Chapter 4
Action Datasets and MHI

Abstract There are a number of benchmark datasets for action, activity, gesture, and gait recognition. In this chapter, we present mainly those which are used to evaluate the MHI or its variants.

4.1 Various Datasets

There are a good number of datasets for various purposes. Although the dimensions and perspective vary from one to other, these datasets become known to the community. However, for the MHI, only few of those are exploited. In this section, we mention the names of various datasets. For detailed explanation on these, one may read the Chap. 6 from [36]. Various datasets are,

- KTH dataset [651]
- Weizmann dataset [601]
- INRIA IXMAS dataset [531]
- CASIA action dataset [131, 133]
- UMD dataset [103]
- ICS Action database [137]
- Korea University Gesture (KUG) database [136, 262]
- Wearable Action Recognition Database (WARD) [135]
- Biological Motion Library (BML) [130]
- HDM05 (Hochschule der Medien) Motion Capture database [129]
- Cambridge Gesture dataset [636]
- Naval Air Training and Operating Procedures Standardization (NATOPS) dataset [128]
- Keck gesture dataset [640]
- YouTube dataset [126]
- YouTube Video dataset [124]
- Hollywood2 Human Action (HOHA) dataset [660]

Md. A. R. Ahad, *Motion History Images for Action Recognition and Understanding*, SpringerBriefs in Computer Science, DOI: 10.1007/978-1-4471-4730-5_4,

- UCF sport action dataset [445]
- Soccer dataset [493]
- Figure-skating dataset—Caltech dataset [176]
- ADL—Assisted Daily Living dataset [139]
- Kisses/Slaps dataset [445]
- UIUC action dataset [104]
- Still image action dataset [172, 173]
- Nursing-home dataset [169]
- Collective Activity dataset [20]
- Coffee and Cigarettes dataset [150]
- People Playing Musical Instrument (PPMI) [175]
- DARPA's Mind's Eye Program [18]
- VIRAT video dataset [125]
- UMN Dataset: Unusual Crowd Activity [165]
- Web dataset [165, 166]
- HumanEva-I/II dataset [108]
- Interaction Dataset for *High-level Human Interaction Recognition Challenge* [19]
- Aerial-view for *Aerial View Activity Classification Challenge* [17]
- Wide-area Activity for *Wide-Area Activity Search and Recognition Challenge* [16]
- Dynamic Hand Posture database [46]
- Humanid Gait Challenge dataset [265]
- TREC Video Retrieval Evaluation: TRECVID [15]
- ChaLearn Gesture Challenge dataset [14]
- MSR Action Dataset of 63 actions [114]
- CMU motion capture database [13]
- Human Motion Database (HMD) at University of Texas at Arlington [123]
- Interactive Emotional Dyadic MoCo (IEMOCAP) database [122]
- Multi-camera Human Action Video dataset [121]
- Manually Annotated Silhouette Data from the MuHAVi dataset [121]
- Virtual Human Action Silhouette (ViHASi) dataset [119, 120, 324]
- POETICON Enacted Scenario Corpus [118]
- TMU Kitchen dataset [117]
- Carnegie Mellon University Multimodal Activity (CMUMMAC) database [116]
- i3DPost Multi-view dataset [115]
- CHIL 2007 Evaluation dataset [113]
- OpenDoor and SitDown-StandUp dataset [112]
- Several databases by Visual Geometry Gr. [111]
- Yilmaz and Shah's dataset [110]
- PETS benchmark dataset—e.g., PETS2006, PETS2007 [109]

Fig. 4.1 Some sample images for KTH dataset. Six actions are sequentially presented from Column1 through Column6 as walking, jogging, running, boxing, hand waving, and hand clapping

4.2 Datasets Employed in MHI

From the above enlisted datasets, only few datasets are tried with the MHI method and its variants. The question may arise—why! In fact, no single method on action recognition is tried with many datasets. Most of the approaches are mainly used by the originators or their groups and in a very few cases, by others. In this regard, the MHI gets much more attention and is explored in various datasets. Apart from the following datasets, it is experimented under various datasets developed by the authors, which are not open for others to use and compare. Therefore, we explore here only the publicly available and well-known datasets that are used in the MHI or its variants.

4.2.1 KTH Dataset

It is the most well-known and compared dataset! The KTH dataset is developed by [651] where only six different actions from a single person are taken by using a single camera. There is a slight camera movement in terms of panning and slight movement—but overall it is a difficult dataset. It has both indoor and outdoor actions of walking, running, jogging, boxing, hand waving, and hand clapping taken from 25 subjects. It has variability in terms of illumination, heights, clothing, directions of motions, presence of shadows, poor lighting, indoor-outdoor, panning of camera, camera movement, varied image depth, and so on. These are taken in four sets.

Figure 4.1 shows some sample frames of this dataset. The most difficult part of this dataset is the walking versus jogging versus running actions—as they overlap more than other actions. Some comparative recognition results are presented in Table 4.1.

Fig. 4.2 Some sample images for Weizmann dataset. Actions are (in *top-row*) run, gallop sideways, skip, jump forward on two legs, jumping in one place on two legs, (in *bottom-row*) bend, jumping jack, walk, waving one hand, and waving both hands

Table 4.1 Average action recognition rate by various methods in KTH dataset

Recognition approach	Average recognition rate (in %)
[60]	97.40
[632]	97.00
[642]	97.00
[146]	95.10
[636]	95.00
[637]	94.50
[140]	94.50
[638]	91.80
[658]	91.40
[452]	90.50
[649]	89.30
[145]	87.70
[646]	86.60
[643]	81.50
[473]	80.99
[651]	71.72

4.2.2 Weizmann Dataset

This is another well-known dataset based on single subject from a static camera. The Weizmann dataset [601] has 90 low-resolution (180×144) videos from nine different subjects, for 10 action classes. These are bend, jumping jack, jump forward, jump in place, run, gallop sideways, skip, walk, wave one hand, and wave both hands. Compared to the KTH dataset, it is very simple, and hence widely exploited. Figure 4.2 presents few images for each action. Some recognition results are shown in Table 4.2.

Table 4.2 Average action recognition rate by various methods in Weizmann dataset

Recognition approach	Average recognition rate (in %)
[2]	100.00
[602]	99.61
[1]	98.8
[146]	97.50
[147]	95.33
[145]	94.74
[12]	94.7
[4]	94.40
[3]	72.8

Table 4.3 Average recognition rate for INRIA IXMAS multi-view action dataset

Recognition approach	Average recognition rate (in %)
[531]	93.3
[743]	75.3
[11]	91.11
[444]	80.6
[324]	77.27

4.2.3 IXMAS Dataset

Above two datasets are based on a single camera. The INRIA IXMAS multi-view action dataset is taken from five synchronized and calibrated cameras, and hence this dataset can be used for view-invariant approaches. The IXMAS dataset [531] has 11 actors, each performing 13 actions with three repetitions. The actions are check watch, cross arms, scratch head, sit down, get up, turn around, walk, wave, punch, kick, point, pick up, and throw. Figure 4.3 shows some frames of this dataset. Table 4.3 shows some results. However, [11] recognize the actions per camera basis and the average recognition results are—65.4, 70.0, 54.3, 66.0, and 33.6 % from camera 1 to 5.

4.2.4 CASIA Gait Database

There is a CASIA action database and CASIA gait database by the Institute of Automation, Chinese Academy of Sciences (CASIA). The CASIA action dataset is a collection of sequences of human activities captured by multi-camera in outdoor environment [131, 133]. Like the above datasets, it has a single person in view for each of the eight actions. Actions are conducted by 24 subjects. The actions are—walk, run, bend, jump, crouch, faint, wander, and punching a car. The dataset also has interactions of two persons for seven different situations. These are—rob, fight,

Fig. 4.3 Some sample images for INRIA IXMAS multi-view action dataset

Fig. 4.4 Some sample images for CASIA gait dataset. Last two frames are from CASIA dataset C (*infra-red* dataset) and others are from set A and set B

follow, follow and gather, meet and part, meet and gather, overtake [132]. On the other hand, in the CASIA gait database there are three different datasets: Dataset A, Dataset B (multi-view dataset), and Dataset C (infrared dataset). Figure 4.4 shows some sample images [131].

However, the CASIA gait dataset is an indoor gait database and comprises 124 subjects. For each subject, there are 10 walking sequences consisting of six normal walking sequences where the subject does not carry a bag or wear a bulky coat (CASIA set A), two carrying bag sequences (CASIA set B) and two wearing coat sequences (CASIA set C) [5]. Each sequence contains multiple gait cycles. Of these sets, set A is simpler than the other two sets. For set A, the result is 99.4 % using the Gait Energy Image (GEI) [297] and 98.3 % using the Gait Entropy Image (GEnI) [5]. This is shown in Table 4.4.

Table 4.4 Average recognition rate with CASIA dataset

Set	Recognition approach	Average recognition rate (in %)
CASIA set A	[297]	99.4
CASIA set A	[5]	98.3
CASIA set B	[297]	60.2
CASIA set B	[5]	80.1
CASIA set C	[297]	30.0
CASIA set C	[5]	33.5

Table 4.5 Some recognition rates with ViHASi dataset

Recognition approach	Average recognition rate (in %)
[119]	98.68
[324]	98.48
[12]	97.6

4.2.5 Virtual Human Action Silhouette (ViHASi) Dataset

The ViHASi—Virtual Human Action Silhouette Dataset is developed for the evaluation of silhouette-based action recognition methods and the evaluation of silhouette-based pose recovery methods [119, 120, 324]. Figure 4.5 shows some sample silhouettes from this dataset.

It consists of 20 action classes from nine actors and up to 40 synchronized perspective camera views. This dataset provides accurate silhouette images, which is usually extracted from raw video sequences, and hence if the silhouettes' extraction are erroneous—then the recognition method will not demonstrate the expected accurate results. Therefore, this dataset is the one to mitigate this problem. They achieve 98.68 % average recognition rate with this dataset. Some comparative recognition results are shown in Table 4.5. Note that these are not the exact rates because, different groups considered different combinations for camera settings, number of subjects, or actions. We put reasonably approximate recognition results in this table. However, using different combinations of cameras, actions, and subjects—the recognition results vary slightly.

4.2.6 CMU MoBo Dataset

The Carnegie Mellon University (CMU) Motion of Body (MoBo) Database [10] is a well-known dataset for gait analysis. It contains 25 individuals walking on a treadmill, for each of four gait types—slow walk, fast walk, ball walk, and inclined walk. The MoBo database is suitable for checking the performance of the shape variation cue compared to the previous shape-only cues. The number of walking cycles is large. The clustered-based Dominant Energy Image (DEI) [302] exploits

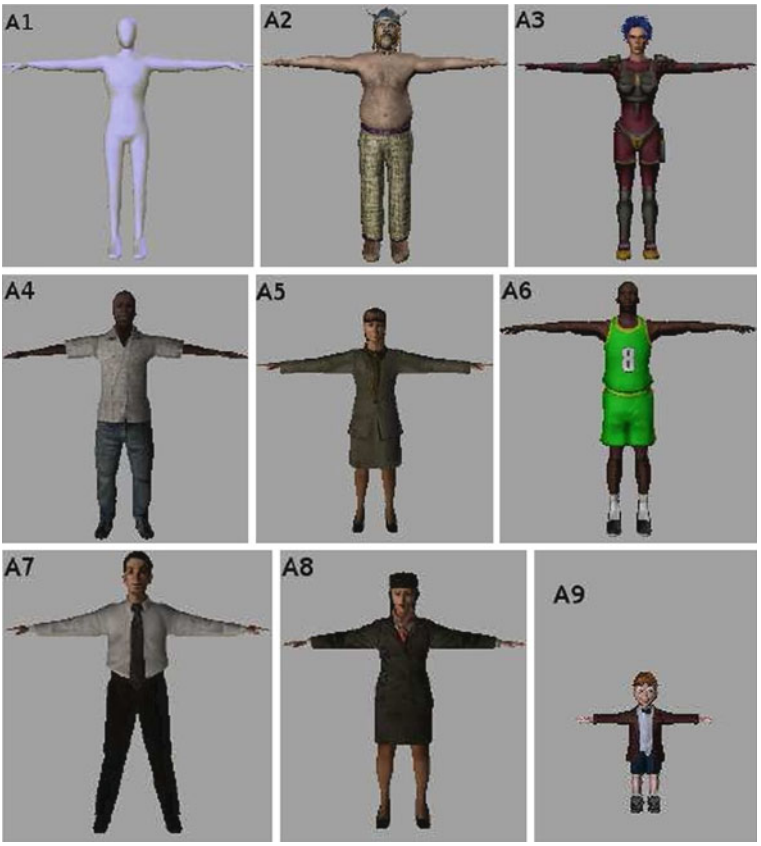

Fig. 4.5 Some sample silhouettes from ViHASi dataset. It demonstrates the diversity of this dataset

the CMU Mobo Gait Database and achieved 82 % recognition accuracy. With Gallery data versus Probe data—various combinations produce different results. Using SVB frieze, average recognition of 84.67 % is achieved for all combinations [9].

4.2.7 USF HumanID Dataset

The USF (University of South Florida) Human ID Gait Challenge Problem [6, 7, 8, 265, 740] consists of a large data set—about 1.2 TB of data related to 1870 sequences from 122 subjects spanning five covariates. The dataset consists of persons walking in elliptical paths in front of the camera(s). Each person walked multiple (≥ 5) circuits around an ellipse, out of which the last circuit forms the dataset. The five covariates for each person are,

- Two different shoe types (A and B)
- Two different carrying conditions (with or without a briefcase)

- On two different surface types (grass and concrete)
- From two different viewpoints (left or right) and
- Some at two different time instants

The baseline algorithm involves silhouette estimation by background subtraction and similarity computation by temporal correlation of the silhouettes. The instructions to get the gait data, the source code of the baseline algorithm, and scripts used to run the challenge experiment are available in there website.

4.2.8 Marcel's Dynamic Hand Poster and Gesture Dataset

A dynamic hand posture and gesture dataset is developed by Marcel [46]. The dataset consists of 15 video sequences for each of the four dynamic hand gestures, which are—Click, No, StopGraspOk, and Rotate. Reference [292] use the MHI with the Fisher Discriminant Analysis (FDA) in this dataset.

4.2.9 TRECVID Dataset

This dataset (TRECVID) is maintained by USA Government for over a decade. Video shot classification is done by considering *Edge Motion History Image* (EMHI) [311, 316]. They choose 60 min CNN video from the TRECVID'05 dataset to estimate all the GMMs in layer 1 and layer 2. Classification topics of video shots are based on the TRECVID'03 dataset, where randomly extracted 100 video shots are considered. Six different classes: indoor, outdoor, news person, news subject, sport, and weather are tested [316]. There is no video shot contains more than one topic. There is no training data and test data are extracted from the same video in each topic [316].

4.3 Conclusion

This chapter is about databases related to action, gesture, and gait recognition. All good datasets are mentioned here. We detail only those datasets that are exploited by the MHI and its variants. However, most of the methods exploit their own datasets and these are not available for researchers to explore and compare. And this chapter concludes this book.

References

1. Jhuang H, Serre T, Wolf L, Poggio T (2007) A biologically inspired system for action recognition. ICCV
2. Ikizler N, Duygulu P (2007) Human action recognition using distribution of oriented rectangular patches. Human motion ICCV
3. Niebles JC, Fei–Fei L (2007) A hierarchical model of shape and appearance for human action classification. IEEE CVPR
4. Thurau C, Hlavac V (2008) Pose primitive based human action recognition in videos or still images. IEEE CVPR
5. Bashir K, Xiang T, Gong S (2009) Gait recognition using gait entropy image. International Conference on Imaging for Crime Detection and Prevention
6. Sarkar S, Jonathon Phillips P, Liu Z, Robledo I, Grother P, Bowyer KW (2005) The human ID gait challenge problem: data sets, performance, and analysis. IEEE Trans Pattern Anal Mach Intell 27(2):162–177
7. Phillips PJ, Sarkar S, Robledo I, Grother P, Bowyer KW (2002) The gait identification challenge problem: data sets and baseline algorithm. International conference on, pattern recognition, pp 385–388
8. Phillips P, Sarkar S, Robledo I, Grother P, Bowyer K (2002) Baseline results for the challenge problem of Human ID using gait analysis. IEEE AFGR
9. Lee S, Liu Y, Collins R (2007) Shape variation-based frieze pattern for robust gait recognition
10. Gross R, Shi J (2001) The CMU motion of body (MoBo) database. Technical report CMU-RI-TR-01-18, robotics institute CMU
11. Weinland D, Boyer E, Ronfard R (2007) Action recognition from arbitrary views using 3D exemplars. ICCV
12. Marin-Jimenez M, Blanca N, Mendoza M (2010) RBM-based silhouette encoding for human action modelling. ICPR
13. CMU Motion Capture Database. http://mocap.cs.cmu.edu
14. ChaLearn Gesture Challenge Dataset. http://gesture.chalearn.org
15. TREC Video Retrieval Evaluation: TRECVID. http://trecvid.nist.gov
16. UT-wide-area DB. http://cvrc.ece.utexas.edu/SDHA2010/Wide_Area_Activity.html
17. UT-Aerial-view DB. http://cvrc.ece.utexas.edu/SDHA2010/Aerial_View_Activity.html
18. DARPA's Minds Eye. http://www.darpa.mil/Our_Work/I2O/Programs/Minds_Eye.aspx
19. UT-Interaction DB. http://cvrc.ece.utexas.edu/SDHA2010/Human_Interaction.html
20. Collective Database. http://www.eecs.umich.edu/vision/activity-dataset.html

Md. A. R. Ahad, *Motion History Images for Action Recognition and Understanding*, SpringerBriefs in Computer Science, DOI: 10.1007/978-1-4471-4730-5,

21. Shen Y, Foroosh H (2009) View-invariant action recognition from point triplets. IEEE transactions PAMI
22. Souvenir R, Babbs J (2008) Learning the viewpoint manifold for action recognition. IEEE Conference, CVPR
23. Parameswaran V, Chellappa R (2003) View invariants for human action recognition. IEEE Conference, CVPR
24. Gong D, Medioni G (2011) Dynamic manifold warping for view invariant action recognition. ICCV
25. Yuedong Y, Aimin H, Qinping Z (2008) View-Invariant action recognition using interest points. ACM MIR
26. Xia L, Chen C, Aggarwal J (2012) View invariant human action recognition using histograms of 3D joints. understanding, modeling, capture and animation, ECCV workshop on human motion
27. Noguchi, Yanai K (2010) A SURF-based spatio-temporal feature for feature- fusion-based action recognition. understanding, modeling, capture and animation, ECCV workshop on human motion
28. Guerra-Filho G, Aloimonos Y (2007) A language for human action. Computer 40:42–51
29. Green R, Guan L (2004) Quantifying and recognizing human movement patterns from monocular video images—part i: a new framework for modeling human motion. IEEE Trans Circuits Syst Video Techn 14:179–190
30. Kulkarni K, Boyer E, Horaud R, Kale A (2010) An unsupervised framework for action recognition using actemes. Asian conference on computer vision
31. Bobick A (1987) Movement, activity, and action: the role of knowledge in the perception of motion. Philos Trans Royal Soc Lond 352:1257–1265
32. Gonzalez J, Varona J, Roca F, Villanueva J (2002) aSpaces: action spaces for recognition and synthesis of human actions. Internatinal workshop on articulated motion and deformable objects
33. Jenkins O, Mataric M (2002) Automated modularization of human motion into actions and behaviors. Technical report CRES-02-002, enter for robotics and embedded systems, University of Southern California
34. Nagel H (1988) From image sequences towards conceptual descriptions. Image Vision Comput 6(2):59–74
35. Kruger V, Kragic D, Ude A, Geib C The meaning of action—a review on action recognition and mapping. IEEE J Select Top Signal Proc
36. Ahad AR Md (2011) Computer vision and action recognition. Atlantic Press, Amsterdam, Paris
37. Holte M, Tran C, Trivedi M, Moeslund T (2011) Human 3D pose estimation and activity recognition from multi-view videos: comparative explorations of recent developments. IEEE J Select Top Signal Proc
38. Turaga P, Veeraraghavan A, Chellappa R (2008) Statistical analysis on stiefel and grassmann manifolds with applications in computer vision. IEEE conference on computer vision and pattern recognition
39. Naiel M, Abdelwahab M, El-Saban M (2011) Multi-view human action recognition system employing 2DPCA. IEEE workshop on applications of computer vision, pp 270–275
40. Roh M, Shin H, Lee S (2010) View-independent human action recognition with volume motion template on single stereo camera. Pattern Recognit Lett 31:639–647
41. Lee C, Chuang C, Hsieh J, Wu M, Fan K (2011) Frame difference history image for gait recognition. International conference on machine learning and, cybernetics, pp 1785–1788
42. Chen C, Liang J, Zhao H, Hu H, Tian J (2009) Frame difference energy image for gait recognition with incomplete silhouettes. Pattern Recognit Lett 30:977–984
43. Xue Z, Ming D, Song W, Wan B, Jin S (2010) Infrared gait recognition based on wavelet transform and support vector machine. Pattern Recognition, 43:2904–2910

44. Liu L, Zheng N, Xiong L (2009) Silhouette quality quantification for gait sequence analysis and recognition. Signal Proc 89:1417–1427
45. Zhou X, Bhanu B (2007) Integrating face and gait for human recognition at a distance in Video. IEEE Trans SMS—part B. Cybernetics 37(5):353–359
46. Marcel S. Dynamic Hand Posture Database. http://www-prima.inrialpes.fr/FGnet/data/10-Gesture/dhp_marcel.tar.gz
47. Yao A, Gall J, Gool L (2012) Coupled action recognition and pose estimation from multiple views. IJCV, 100(1):16–37
48. Lam T, Lee R, Zhang D (2007) Human gait recognition by the fusion of motion and static spatio-temporal templates. Pattern Recognit 40:2563–2573
49. Triggs B (1998) Autocalibration from planar scenes. European conference on computer vision, pp 89–105
50. Stein G (1995) Accurate internal camera calibration using rotation, with analysis of sources of error. international conference on computer vision, pp 230–236
51. Caprile B, Torre V (1990) Using vanishing points for camera calibration. Intl J Compur Vis 4(2):127–140
52. Liebowitz D, Zisserman A (1998) Metric rectification for perspective images of planes. In Proceeding IEEE conference on computer vision and pattern recognition, pp 482–488, Santa Barbara, California
53. Hartley RI (1994) An algorithm for self calibration from several views. In Proceeding IEEE conference on computer vision and, pattern recognition, pp 908–912
54. Luong Q-T, Faugeras O (1997) Self-calibration of a moving camera from point correspondences and fundamental matrices. Int J Comp Vis 22(3):261–289
55. Maybank SJ, Faugeras OD (1992) A theory of selfcalibration of a moving camera. Int J Comp Vis 8(2):123–152
56. Tsai R (1987) A versatile camera calibration technique for high-accuracy 3D machine vision metrology using off-the-shelf tv cameras and lenses. IEEE J Robotics Autom 3(4):323–344
57. Zhang Z (1999) Flexible camera calibration by viewing a plane from unknown orientations, IEEE
58. Blake R, Shiffrar M (2007) Perception of human motion. Ann Rev Psychol 58(1):47–73
59. Castrodad A, Sapiro G (2012) Sparse modeling of human actions from motion imagery. IJCV 100(1):1–15
60. Guo K, Ishwar P, Konrad J (2010) Action recognition using sparse representation on covariance manifolds of optical flow. IEEE international conference on advanced video and signal based surveillance
61. Ahad M, Tan J, Kim H, Ishikawa S (2011) Approaches for global-based action representations for games and action understanding. IEEE Automatic Face and Gesture Recognition, pp 753–758
62. Rosten E, Drummond T (2005) Fusing points and lines for high performance tracking. International conference on computer vision
63. Chen C, Aggarwal J (2009) Recognizing human action from a far field of view. IEEE workshop on motion and video computing
64. Willamowski J, Arregui D, Csurka G, Dance C, Fan L (2004) Categorizing nine visual classes using local appearance descriptors. IWLAVS
65. Matikainen P, Hebert M, Sukthankar R (2009) Trajectons: action recognition through the motion analysis of tracked features. VOEC workshop
66. Bosch A, Zisserman A, Munoz X (2007) Image classification using random forests and ferns. International conference on computer vision
67. Sun Z, Tan T (2009) Ordinal measures for iris recognition. IEEE transaction pattern analysis and machine intelligence
68. Fawcett T (2006) An introduction to ROC analysis. Pattern Recognit Lett 27:861–874

69. Wang X, Tang X (2004) Random sampling LDA for face recognition. IEEE Computer Vision and Pattern Recognition
70. Mallapragada P, Rong J, Jain A, Yi L (2009) SemiBoost: boosting for semi-supervised learning. IEEE transaction pattern analysis and machine intelligence
71. Pavlidis I, Morellas V, Tsiamyrtzis V, Harp S (2001) Urban surveillance systems: from the laboratory to the commercial world. Proceedings of the IEEE pp 1478–1497
72. Lo B, Velastin S (2001) Automatic congestion detection system for underground platforms. International symposium on intell. multimedia, video and speech processing pp 158–161
73. Cucchiara R, Grana C, Piccardi M, Prati A (2003) Detecting moving objects, ghosts and shadows in video streams. IEEE Trans Pattern Anal Mach Intell 25(10):1337–1342
74. Han B, Comaniciu D, Davis L (2004) Sequential kernel density approximation through mode propagation: applications to background modeling. Asian conference on computer vision
75. Oliver N, Rosario B, Pentland A (2000) A Bayesian computer vision system for modeling human interactions. IEEE Trans Pattern Anal Mach Intell 22(8):831–843
76. Liu X (2009) Discriminative face alignment. IEEE trans, Pattern analysis and machine intelligence
77. Hsu C, Lin C (2002) A comparison of methods for multiclass, support vector machines. IEEE Trans Neural Netw 13(2):415–425
78. Vapnik V (1998) Statistical learning theory. Wiley Publications, New York
79. Gleicher M (1999) Animation from observation: motion capture and motion editing. Comp Graph 33:51–54
80. Horn B (2000) Tsai's camera calibration method revisited. http://people.csail.mit.edu/bkph/articles/Tsai_Revisited.pdf
81. Abdel-Aziz Y, Karara H (1971) Direct linear transformation from comparator coordinates into object space coordinates in close-range photogrammetry. Symposium on close-range photogrammetry, pp 1–18
82. Hartley R, Zisserman A (2004) Multiple view geometry in computer vision. Cambridge University Press, Cambridge
83. Chum O, Matas J (2005) Matching with PROSAC—progressive sample consensus. IEEE Comp Vis Pattern Recognit 1:220–226
84. Nister D (2003) Preemptive RANSAC for live structure and motion estimation. International Conference on Computer Vision 1
85. Matas J, Chum O, Urba M, Pajdla T (2002) Robust wide baseline stereo from maximally stable extremal regions. British Machine Vision Conference
86. Belongie S, Malik J (2000) Matching with shape contexts. IEEE workshop on contentbased access of image and video libraries
87. Viola P, Jones M (2001) Rapid object detection using boosted cascade of simple features. IEEE computer vision and pattern recognition
88. Piccardi M (2004) Background subtraction techniques: a review. IEEE international conference on systems, Man and cybernetics
89. Bouwmans T (2009) Subspace learning for background modeling: a survey. Recent Pat Comp Sci 2(3):223–234
90. Elhabian S, El-Sayed E, Ahmed S (2008) Moving object detection in spatial domain using background removal techniques-state-of-art. Recent patents on computer science
91. Sarfraz S, Hellwich O (2008) Head pose estimation in face recognition across pose scenarios. International conference on computer vision theory and applications, pp 235–242
92. Kim S, Yoon K, Kweon I (2006) Object recognition using a generalized robust invariant feature and Gestalt's law of proximity and similarity. IEEE computer vision and pattern recognition workshop
93. Lazebnik S, Schmid C, Ponce J (2004) Semi-local affine parts for object recognition. British machine vision conference

94. Lowe D (1999) Object recognition from local scale-invariant features. Int Conf Comp Vis 2:1150–1157 (L. 2007)
95. Deng H, Zhang W, Mortensen E, Dietterich T, Shapiro L (2007) Principal curvature-based region detector for object recognition. IEEE computer vision and pattern recognition
96. Wang H, Brady M (1995) Real-time corner detection algorithm for motion estimation. Image Vis Comput 13(9):695–703
97. Mikolajczyk K, Schmid C (2004) Scale and affine invariant interest point detectors. Int J Comp Vis 60(1):63–86
98. Harris C, Stephens M (1988) A combined corner and edge detector. 4th alvey vision conference, pp 147–151
99. Trajkovic M, Hedley M (1998) Fast corner detection. Image Vis Comput 16(2):75–87
100. Smith S, Brady J (1997) SUSAN—a new approach to low level image processing. Int J Comp Vis 23:45–78
101. Sridhar M, Cohn A, Hogg D (2010) Discovering an event taxonomy from video using qualitative spatio-temporal graphs. European conference on artificial intelligence
102. Guan P, Freifeld O, Black M (2010) A 2D human body model dressed in eigen clothing. European conference on computer vision
103. Veeraraghavan A, Chellappa R, Roy-Chowdhury A (2006) The function space of an activity. IEEE computer vision and pattern recognition
104. Tran D, Sorokin A (2008) Human activity recognition with metric learning. European conference on computer vision
105. Thioux M, Gazzola V, Keyesers C (2008) Action understanding: how, what and why. Current biology 18(10):171–179
106. Yamane K, Nakamura Y (2010) Human motion database with a binary tree and node transition graphs. J Auton Robots 29(2):502–528
107. Ahad M, Tan J, Kim H, Ishikawa S (2011) Action dataset—a survey. SICE annual conference
108. Sigal L, Balan A, Black M (2010) HumanEva: synchronized video and motion capture dataset and baseline algorithm for evaluation of articulated human motion. Int J Comp Vis 87:1–2
109. PETS (2007) Workshops on Performance Evaluation of Tracking & Surveillance (PETS). http://www.cvg.rdg.ac.uk/PETS2007/data.html
110. Yilmaz A, Shah M (2005) Recognizing human actions in videos acquired by uncalibrated moving cameras. International conference on computer vision
111. Patron-Perez A, Marszalek M, Zisserman A, Reid I (2010) High five: recognising human interactions in TV shows. British machine vision conference
112. Duchenne O, Laptev I, Sivic J, Bach F, Ponce J (2009) Automatic annotation of human actions in video international conference on computer vision
113. Burger S (2008) The CHIL RT07 evaluation data. Multimodal technologies for perception of humans
114. MSR action dataset. http://research.microsoft.com/en-us/um/people/zliu/actionrecorsrc/default.htm
115. Gkalelis N, Kim H, Hilton A, Nikolaidis N, Pitas I (2009) The i3DPost multi-view and 3D human action/interaction database. Conference on visual media production
116. Hodgins F, Macey J (2009) Guide to the Carnegie Mellon University multimodal activity (cmu-mmac), database. CMU-RI-TR-08-22
117. Tenorth M, Bandouch J, Beetz M (2009) The TUM kitchen data set of everyday manipulation activities for motion tracking and action recognition. IEEE international workshop on tracking humans for the evaluation of their motion in image sequences with international conference on computer vision
118. Wallraven C, Schultze M, Mohler B, Vatakis A, Pastra K (2011) The POETICON enacted scenario corpus—a tool for human and computational experiments on action understanding. IEEE automatic face and gesture recognition. http://poeticoncorpus.kyb.mpg.de

119. Ragheb H, Velastin S, Remagnino P, Ellis T (2008) ViHASi: virtual human action silhouette data for the performance evaluation of silhouette-based action recognition methods workshop on activity monitoring by multi-camera surveillance systems
120. ViHASi Virtual Human Action Silhouette (ViHASi) database. http://dipersec.king.ac.uk/VIHASI/
121. MuHAVi. http://dipersec.king.ac.uk/MuHAVi-MAS
122. Busso C, Bulut M, Lee C, Kazemzadeh A, Mower E, Kim S, Chang J, Lee S, Narayanan S (2008) IEMOCAP: interactive emotional dyadic motion capture database. Lang Res Eval 42(4):335–359
123. Guerra-Filho G, Biswas A (2011) The human motion database: a cognitive and parametric sampling of human motion. IEEE automatic face and gesture recognition
124. Niebles J, Han B, Ferencz B, Fei-Fei L (2008) Extracting moving people from internet videos. European conference on computer vision
125. VIRAT (2011) VIRAT database. http://www.viratdata.org
126. Liu J, Luo J, Shah M (2009) Recognizing realistic actions from videos ''in the wild''. IEEE computer vision and pattern recognition
127. Keck gesture database. http://www.umiacs.umd.edu/~shivnaga/supplmat_ActionRecBallisticDyn_CVPR08/action_rec_using_ballistic_dynamics.html#gesture_rec
128. Song Y, Demirdjian D, Davis R (2011) Tracking body and hands for gesture recognition: NATOPS aircraft handling signals database. IEEE Autom Face Gesture Recognit
129. Muller M, Ryder T, Clausen M, Eberhardt B, Kruger B, Weber A (2007) Documentation: Mocap database HDM05. Universitat Bonn, Technical report CG-2007-2
130. Ma Y, Paterson H, Pollick F (2006) A motion capture library for the study of identity, gender, and emotion perception from biological motion. Behav Res Methods 38:134–141
131. CASIA Database. http://www.cbsr.ia.ac.cn/english/Action%20Databases%20EN.asp
132. Zhang Z, Huang K, Tan T (2008) Multi-thread parsing for recognizing complex events in videos. European conference on computer vision
133. Wang Y, Huang K, Ta T (2007) Human activity recognition based on R transform. IEEE computer vision and pattern recognition
134. WAR. http://www.eecs.berkeley.edu/
135. Yang A, Jarafi R, Kuryloski P, Iyengar S, Sastry S, Bajcsy R (2008) Distributed segmentation and classification of human actions using a wearable motion sensor network. Workshop on human communicative behavior analysis with computer vision and pattern recognition
136. Hwang B, Kim S, Lee S (2006) A full-body gesture database for automatic gesture recognition. IEEE automatic face and gesture recognition
137. ICS Action Database, The University of Tokyo. http://www.ics.t.u-tokyo.ac.jp/action
138. Vasconcelos M, Vasconcelos N (2009) Natural image statistics and low-complexity feature selection. IEEE Trans Pattern Anal Mach Intell 31(2):228–244
139. Messing R, Pal C, Kautz H (2009) Activity recognition using the velocity histories of tracked keypoints. International conference on computer vision
140. Gilbert A, Illingworth J, Bowden R (2010) Action recognition using mined hierarchical compound features. IEEE trans, Pattern analysis and machine intelligence
141. Yaffet L, Wolf L (2009) Local trinary patterns for human action. International conference on computer vision
142. Raptis M, Soatto S (2010) Tracklet descriptors for action modeling and video analysis. European conference on computer vision
143. Bregonzio M, Li J, Gong S, Xiang T (2010) Discriminative topics modelling for action feature selection and recognition. British machine vision conference
144. Liu G, Zhang J, Wang W, McMillan L (2005) A system for analyzing and indexing human—motion databases. SIGMOD
145. Ali S, Shah M (2010) Human action recognition in videos using kinematic features and multiple instance learning. IEEE Trans Pattern Anal Mach Intell 32(2):288–303

146. Seo H, Milanfar P (2011) Action recognition from one example. IEEE trans, Pattern analysis and machine intelligence
147. Junejo I, Dexter E, Laptev I, Perez P (2011) View-independent action recognition from temporal self-similarities. IEEE Trans Pattern Anal Mach Intell 33:172–185
148. Satkin S, Hebert M (2010) Modeling the temporal extent of actions.European conference on computer vision
149. Schindler K, Van Gool L (2008) Action snippets: How many frames does human action recognition require. IEEE Comp Vis Pattern Recognit
150. Gaidon A, Harchaoui Z, Schmid C (2011) Actom sequence models for efficient action detection. IEEE computer vision and pattern recognition
151. Fischler M, Bolles R (1981) Random sample consensus: a paradigm for model fitting with applications to image analysis and automated cartography. Commun ACM 24(6):381–395
152. Chen Y, Dang X, Peng H, Bart H (2009) Outlier detection with the kernelized spatial depth function. IEEE trans, Pattern analysis and machine intelligence
153. Friedman J (1989) Regularized discriminant analysis. J Am Stat Assoc
154. Bensmail H, Celeux G (1996) Regularized Gaussian discriminant analysis through Eigenvalue decomposition. J Am Stat Assoc
155. Bouveyron C, Girard S, Schmid C (2007) High dimensional discriminant analysis. Communication in statistics, theory and methods
156. Tao D, Ji X, Wu X, Maybank S (2009) Geometric mean for subspace selection. IEEE trans, Pattern analysis and machine intelligence
157. Lolitkar R, Kothari R (2000) Fractional-step dimensionality reduction. IEEE trans, Pattern analysis and machine intelligence
158. Sanja F, Skocaj D, Leonardis A (2006) Combining reconstructive and discriminative subspace methods for robust classification and regression by subsampling. IEEE trans, Pattern analysis and machine intelligence
159. Kim J, Choi J, Yi J, Turk M (2005) Effective representation using ICA for face recognition robust to local distortion and partial occlusion. IEEE Trans Pattern Anal Mach Intell 27(12):1977–1981
160. Belhumeur P, Hesanha J, Kreigman D (1997) Eigenfaces vs Recognition using class specific linear projection. IEEE trans pattern analysis and machine intelligence, Fisherfaces
161. Li S, Hou X, Zhang H, Cheng Q (2001) Learning spatially localized, parts-based representation. IEEE computer vision and pattern recognition
162. Ho J, Yang M, Lim J, Lee K, Kriegman D (2003) Clustering appearances of objects under varying illumination conditions. IEEE computer vision and pattern recognition
163. Wright J, Yang A, Ganesh A, Sastry S, Ma Y (2009) Robust face recognition via sparse representation. IEEE trans, Pattern analysis and machine intelligence
164. Zhang X, Fan G (2010) Dual gait generative models for human motion estimation from a single camera. IEEE transaction on systems, man, and cybernetics, part B. Cybernetics 40(4):1034–1049
165. Mehran R, Oyama A, Shah M (2009) Abnormal crowd behavior detection using social force model. IEEE computer vision and pattern recognition
166. Web dataset, UCF Web Dataset. http://www.cs.ucf.edu/~ramin/?page_id=24#2.Experiments_on_Web_Dataset
167. Mehran R, Moore B, Shah M (2010) A streakline representation of flow in crowded scenes. European conference on computer vision
168. Niebles J, Wang H, Fei-Fei L (2006) Unsupervised learning of human action categories using spatial-temporal words. British machine vision conference
169. Lan T, Wang Y, Mori G, Robinovitc S (2010) Retrieving actions in group contexts. International workshop on sign gesture activity with European conference on computer vision
170. Lan T, Wang Y, Yang W, Mori G (2010) Beyond actions: Discriminative models for contextual group activities. Neural information processing systems (NIPS)

171. Lan T, Wang Y, Mori G (2011) Discriminative figure-centric models for joint action localization and recognition. International conference on computer vision
172. Ikizler N, Cinbis R, Pehlivan S, Duygulu P (2008) Recognizing actions from still images. International conference on pattern recognition
173. Ikizler N, Cinbis R, Sclaroff S (2009) Learning actions from the web. International conference on computer vision
174. Yang W, Wang Y, Mori G (2010) Recognizing human actions from still images with latent poses. IEEE Comp Vis Pattern Recognit
175. Yao B, Fei-Fei L (2010) A structured image representation for recognizing human and object interactions. IEEE computer vision and pattern recognition
176. Wang Y, Jiang H, Drew M, Li Z, Mori G (2008) Unsupervised discovery of action classes. IEEE computer vision and pattern recognition
177. Fanti C (2008) Towards automatic discovery of human movemes. PhD Thesis, California Institute of Technology. http://www.vision.caltech.edu/publications/phdthesis_fanti.pdf
178. Del Vecchio D, Murray R, Perona P (2002) Primitives for human motion: a dynamical approach. IFAC world congress on automatic control
179. Bregler C, Malik J (1997) Learning and recognizing human dynamics in video sequences. IEEE computer vision and, pattern recognition, pp 568–674
180. Goncalves L, Di Bernardo E, Perona P (1998) Reach out and touch space (motion learning). IEEE Automatic Face and Gesture Recognition, pp 234–239
181. Song Y, Goncalves L, Perona P (2001) Unsupervised learning of human motion models. Advances in neural information processing systems (NIPS)
182. Wang Y, Mori G (2011) Hidden part models for human action recognition: probabilistic vs. max-margin. IEEE Transaction on Pattern Analysis and Machine Intelligence
183. Choi W, Shahid K, Savarese S (2011) Learning context for collective activity recognition. IEEE computer vision and pattern recognition
184. Choi W, Shahid K, Savarese S (2009) What are they doing? Collective activity classification using spatio-temporal relationship among people. International workshop on visual surveillance (VSWS09) with international conference on computer vision
185. Murase H, Lindenbaum M (1995) Partial eigenvalue decomposition of large images using spatial temporal adaptive method. IEEE Trans Image Proc 4(5):622–629
186. Rahman M, Ishikawa S (2005) Human posture recognition: eigenspace tuning by mean eigenspace. Int J Image Graph 5(4):825–837
187. Viola P, Jones M (2000) Robust real-time object detection. IEEE workshop on statistical and computational theories of vision
188. Black M, Jepson A (1998) Eigen tracking: robust matching and tracking of articulated objects using view-based representation. Int J Comp Vis 26(1):63–84
189. Ohba K, Ikeuchi K (1997) Detectability, uniqueless and reliability of eigen windows for stable verifications of partially occluded objects. IEEE Trans Pattern Anal Mach Intell 9:1043–1047
190. Murase H, Nayar K (1995) Visual learning and recognition of 3-D objects from appearance. Int J Comp Vis 14:39–50
191. Li Z, Wang K, Li L, Wang F (2006) A review on vision-based pedestrian detection for intelligent vehicles. ICVES, pp 57–62
192. MIAC-JP. Ministry of Internal Affairs and Communications, JAPAN. http://www.stat.go.jp/english/data/nenkan/1431-26.htm
193. The World Bank. http://www.worldbank.org/html/fpd/transport/roads/safety.htm
194. Krotosky S, Trivedi M (2007) On color-, infrared-, and multimodal-stereo approaches to pedestrian detection. IEEE Trans ITS 8(4):619–629
195. Zhang Z, Faugeras O (1992) Three-dimensional motion computation and object segmentation in a long sequence of stereo frames. Int J Comp Vis 7:211–241
196. Chang Y, Aggarwal J (1991) 3D structure reconstruction from an ego motion sequence using statistical estimation and detection theory.Workshop on visual motion

197. Sethi I, Jain R (1987) Finding trajectories of feature points in a monocular image sequence. IEEE Trans Pattern Anal Mach Intell 9:56–73
198. Cui N, Weng J, Cohen P (1990) Extended structure and motion analysis from monocular image sequences. International conference on computer vision, pp 222–229
199. Weng J, Ahuja N, Huang T (1992) Matching two perspective views. IEEE Trans Pattern Anal Mach Intell 14:806–825
200. Tomasi C, Kanade T (1991) Detection and tracking of point features. Carnegie Mellon University, Technical report CMU-CS-91-132
201. Hager G, Belhumeur P (1996) Real-time tracking of image regions with changes in geometry and illumination. IEEE computer vision and, pattern recognition, pp 403–410
202. Tommasini T, Fusiello A, Trucco E, Roberto V (1998) Making good features track better. IEEE computer vision and pattern recognition
203. Shi J, Tomasi C (1994) Good features to track. IEEE computer vision and pattern recognition
204. Yao Y, Chellappa R (1995) Tracking a dynamic set of feature points. IEEE Trans Image Proc 4(10):1382–1395
205. Yao Y, Chellappa R (1994) Dynamic feature point tracking in an image sequence. IAPR Comp Vis Pattern Recognit 1:654–657
206. Naito Y, Okatani T, Deguchi K (2003) Comparison of the feature point tracking method in image sequences. SICE annual conference pp 1326–1331
207. Wang Y, Cao L, Huang W (2003) 3-D human motion estimation using regularization with 2-d feature point tracking. International conference on machine learning and, cybernetics pp 2931–2935
208. Borgefors G (1988) Hierarchical chamfer matching: a parametric edge matching algorithm. IEEE Trans Pattern Anal Mach Intell 10(6):849–865
209. Peterson L (2009) K-nearest neighbor. http://www.scholarpedia.org/article/K-nearest_neighbor 4:2
210. Weinberger K, Blitzer J, Saul L (2005) Distance metric learning for large margin nearest neighbor classification. Annual conference on neural information processing systems
211. Aguiar P, Moura J (2000) Weighted factorization. International conference on image processing pp 549–562
212. Li Y, Brooks M (1999) An efficient recursive factorization method for determining structure from motion. IEEE computer vision and, pattern recognition, pp 138–143
213. Fujiki J, Kurata T (2000) Recursive factorization method for the paraperspective model based on the perspective projection. International conference on, pattern recognition, pp 406–410
214. Fujiki J, Kurata T, Tanaka M (1998) Iterative factorization method for object recognition. International symposium on electronic, imaging, pp 192–201
215. Quan L, Kanade T (1996) A factorization method for affine structure from line correspondences. IEEE computer vision and, pattern recognition, pp 803–808
216. Ueshiba T, Tomita F (1998) A factorization method for projective and Euclidean reconstruction from multiple perspective views via iterative depth estimation. European conference on computer vision pp 296–210
217. Sturm P, Triggs B (1996) A factorization based algorithm for multi-image projective structure and motion. European conference on computer vision, pp 709–720
218. Christy S, Horaud R (1996) Euclidean reconstruction: from paraperspective to perspective. Europ Conf Comp Vis 2:129–140
219. Aguiar P, Moura J (1999) Factorization as a rank 1 problem. IEEE Comp Vis Pattern Recognit 1:178–184
220. Aguiar P, Moura J (1999) A fast algorithm for rigid structure from image sequences. Int Conf Image Proc 3:125–129
221. Aguiar P, Moura J (1998) Video representation via 3D shaped mosaics. Int Conf Image Proc 1:823–827

222. Guerreiro R, Aguiar P (2002) Factorization with missing data for 3D structure recovery. IEEE workshop on multimedia, signal processing, pp 105–108
223. Aguiar P, Moura J (2001) Three-dimensional modeling from two-dimensional video. IEEE Trans Image Proc 10:1541–1551
224. Nakamura K, Saito H, Ozawa S (2000) 3D reconstruction of book surface taken from image sequence with handy camera. Int Conf Pattern Recognit 4:575–578
225. Costeria J, Kanade T (1998) A multi-body factorization method for independently moving objects. Int J Comp Vis 29:159–178
226. Sugaya Y, Kanatani K (2002) Outlier removal for feature tracking by subspace separation. Symposium on sensing via imaging, Info, pp 603–608
227. Huynh D, Hartley R, Heyden A (2003) Outlier correction in image sequences for the affine camera. International conference on computer vision, pp 585–590
228. Huynh D, Heyden A (2001) Outlier detection in video sequences under affine projection. IEEE computer vision and pattern recognition, pp 695–701
229. Ke Q, Kanade T (2003) A robust subspace approach to extracting layers from image sequences. Ph.D. Thesis, Carnegie Mellon University
230. Hawkins D, Liu L, Young S Robust singular value decomposition. http://www.niss.org/technicalreports/tr122.pdf
231. Hwang K, Yokoya N, Takemura H, Yamazawa K (1998) A factorization method using 3-D linear combination for shape and motion recovery. Int Conf Pattern Recognit 2:959–963
232. Yu H, Chen Q, Xu G, Yachida M (1996) 3D shape and motion by SVD under higher-order approximation of perspective projection. International conference on, pattern recognition, pp 456–460
233. Xi L (2004) 3D orthographic reconstruction based on robust factorization method with outliers. International conference on image processing, pp 1927–1930
234. Morita T, Kanade T (1997) A sequential factorization method for recovering shape and motion from image streams. IEEE Trans Pattern Anal Mach Intell 19:858–867
235. Branco C, Costeira J (1998) A 3D image mosaicing system using the factorization method. IEEE Int Symp Ind Electr 2:674–678
236. Guerreiro R, Aguiar P (2002) 3D structure from video streams with partially overlapping images. Int Conf Image Proc 3:897–900
237. Tan J, Ishikawa S (1999) Extracting 3-D motions of individuals at work by uncalibrated multiple video cameras. Int Conf Syst Man Cybern 3:487–490
238. Kurata T, Fujiki J, Kourogi K, Sakaue K (2000) A fast and robust approach to recovering structure and motion from live video frames. IEEE Comp Vis Pattern Recognit 2:528–535
239. Yamaguchi J, Tan J, Ishikawa S (2005) A mobile motion capture system employing image transfer. IEEE TENCON
240. Poelman C, Kanade T (1997) A paraperspective factorization method for shape and motion recovery. IEEE Trans Pattern Anal Mach Intell 19:206–218
241. Tan J, Ishikawa S (2001) Deformable shape recovery by factorization based on a spatiotemporal measurement matrix. Comp Vis Image Underst 82:101–109
242. Tan J, Ishikawa S (2000) On modeling three-dimensional objects by uncalibrated cameras. IEEE TENCON 1:59–63
243. Tomasi C, Kanade T (1992) Shape and motion from image streams under orthography: a factorization method. Int J Comp Vis 9:137–154
244. Djouabi A, Bouktache E (1997) A fast algorithm for the nearest-neighbor classifier. IEEE Trans Pattern Anal Mach Intell 19:277–281
245. Fukunaga K (1985) The estimation of the Bayes error by the k-nearest neighbor approach. In: Kanal L, Rosenfeld A (eds) Progress in pattern recognition, vol 2. Elsevier Science Publishers, London, pp 169–187
246. Forsyth D, Ponce J (2003) Computer vision—a modern approach. Prentice-Hall, Englewood Cliffs

247. Cover T, Hart P (1967) Nearest neighbor pattern classification. IEEE Trans Inf Theory 13:21–27
248. Song Y, Huang J, Zhou D, Zha H, Giles C (2007) IKNN: informative k-nearest neighbor pattern classification. LNAI 4702:248–264
249. Prokop R, Reeves A (1992) A survey of moment-based techniques for unoccluded object representation and recognition. CVGIP: graphical Models Image Proc 54:438–460
250. Dudani S, Breeding K, McGhee R (1977) Aircraft identification by moment invariants. IEEE Trans Comp 26:39–45
251. Sanz P, Marin R, Sanchez J (2005) Including efficient object recognition capabilities in online robots: from a statistical to a neural-network classifier. IEEE Trans SMC Appl Rev 35:87–96
252. Devroye L, Gyorfi L, Lugosi G (1996) A probabilistic theory of pattern recognition. Applications of mathematics—stochastic modelling and applied probability
253. Jozwik A, Serpico S, Roli F (1998) A parallel network of modified 1-NN and k-NN classifiers—application to remote-sensing image classification. Pattern Recognit Lett 19:57–62
254. Sarkar M (2007) Fuzzy-rough nearest neighbor algorithms in classification. Fuzzy Sets Syst 158:2134–2152
255. Bishop C (1995) Neural networks for pattern recognition. Oxford University Press, Oxford
256. Flusser J, Zitova B, Suk T, Moments and moment invariants in image analysis. http://staff.utia.cas.cz/zitova/tutorial/
257. Li Y (1992) Reforming the theory of invariant moments for pattern recognition. Pattern Recognit 25:723–730
258. Maitra S (1979) Moment invariants. IEEE 67:697–699
259. Reiss T (1991) The revised fundamental theorem of moment invariants. EEE Trans Pattern Anal Mach Intell 13:830–834
260. Shutler J, Statistical moments, University of Southampton, UK, Tutorial http://homepages.inf.ed.ac.uk/rbf/CVonline/LOCAL_COPIES/SHUTLER3/CVonline_moments.html
261. Sziranyi T, with other partners UPC, SZTAKI, Bilkent and ACV. Real time detector for unusual behavior. http://www.muscle-noe.org/content/view/147/64/
262. Full-body gesture database. http://gesturedb.korea.ac.kr/
263. Kellokumpu V, Pietikainen M, Heikkila J (2005) Human activity recognition using sequences of postures. Machine vision and applications, pp 570–573
264. Yu S, Tan D, Tan T (2006) A framework for evaluating the effect of view angle, clothing and carrying condition on gait recognition. International conference on, pattern recognition, pp 441–444
265. Sarkar S, Phillips P, Liu Z, Vega I, Grother P, Bowyer K (2005) The humanid gait challenge problem: data sets, performance, and analysis. IEEE Trans Pattern Anal Mach Intell 27:162–177
266. The Inria XMAS (IXMAS) motion acquisition sequences. https://charibdis.inrialpes.fr
267. Ahad A, Ogata T, Tan J, Kim H, Ishikawa S (2007) A smart automated complex motion recognition technique. Workshop on multi-dimensional and multi-view image processing with Asian conference on computer vision, pp 142–149
268. Spengler M, Schiele B (2003) Towards robust multi-cue integration for visual tracking. Mach Vis Appl 14:50–58
269. Piater J, Crowley J (2001) Multi-modal tracking of interacting targets using Gaussian approximations. IEEE workshop on performance evaluation of tracking and surveillance with computer vision and, pattern recognition, pp 141–147
270. Kumar S, Kumar D, Sharma A, McLachlan N (2003) Classification of hand movements using motion templates and geometrical based moments. International conference on intelligent sensing and information processing, pp 299–304
271. Ryu W, Kim D, Lee H, Sung J, Kim D (2006) Gesture recognition using temporal templates. International conference on pattern recognition, demo program

272. Ruiz-del-Solar J, Vallejos P (2004) Motion detection and tracking for an AIBO robot using camera motion compensation and Kalman filtering. RoboCup International Symposium, pp 619–627
273. Valstar M, Patras I, Pantic M (2004) Facial action recognition using temporal templates. IEEE workshop on robot and human interactive, communication, pp 253–258
274. Leman K, Ankit G, Tan T (2005) PDA-based human motion recognition system. Int J Softw Eng Knowl 2:199–205
275. Dollar P, RabaudV, Cottrell G, Belongie S (2005) Behavior recognition via sparse spatiotemporal features. International workshop on visual surveillance and performance evaluation of tracking and surveillance, pp 65–72
276. Shin H, Lee S, Lee S (2005) Real-time gesture recognition using 3D motion history model. Conf Intell Comput LNCS 3644:888–898
277. Davis J (2004) Sequential reliable-inference for rapid detection of human actions. IEEE workshop on detection and recognition of events in video
278. Lo C, Don H (1989) 3-D moment forms: their construction and application to object identification and positioning. IEEE Trans Pattern Anal Mach Intell 11:1053–1063
279. Weinland D, Ronfard R, Boyer E (2006) Automatic discovery of action taxonomies from multiple views. IEEE computer vision and, pattern recognition, pp 1639–1645
280. Canton-Ferrer C, Casas J, Pardas M, Sargin M, Tekalp A (2006) 3D human action recognition in multiple view scenarios. Jornades de Recerca en Automatica, Visi. Robotica
281. Petras I, Beleznai C, Dedeoglu Y, Pardas M et al. (2007) Flexible test-bed for unusual behavior detection. ACM conference image and video retrieval, pp 105–108
282. Dalal N, Triggs B (2005) Histograms of oriented gradients for human detection. IEEE computer vision and, pattern recognition, pp 886–893
283. Dalal D, Triggs B, Schmid C (2006) Human detection using oriented histograms of flow and appearance. European conference on computer vision, pp 428–441
284. Kadir T, Brady M (2001) Scale, saliency and image description. Int J Comp Vis 45(1): 83–105
285. Davis J (1998) Recognizing movement using motion histograms. MIT Media Lab. Perceptual computing section technical report, p 487
286. Senior A, Tosunoglu S (2005) Hybrid machine vision control. Florida conference on recent advances in robotics
287. Wong S, Cipolla R (2005) Continuous gesture recognition using a sparse Bayesian classifier. Int Conf Pattern Recognit 1:1084–1087
288. Wong S, Cipolla R (2005) Real-time adaptive hand motion recognition using a sparse Bayesian classifier. International conference on computer vision, workshop, pp 170–179
289. Ng J, Gong S (2001) Learning pixel-wise signal energy for understanding semantics. British machine vision conference, pp 695–704
290. Ng J, Gong S (2003) Learning pixel-wise signal energy for understanding semantics. Image Vis Comput 21:1183–1189
291. Albu A, Trevor B, Naznin V, Beach C (2007) Analysis of irregularities in human actions with volumetric motion history images. IEEE workshop on motion and video computing
292. Alahari K, Jawahar C (2006) Discriminative actions for recognizing events. Indian conference on computer vision, graphics and image processing, pp 552–563
293. Meng H, Pears N, Freeman M, Bailey C (2009) Motion history histograms for human action recognition. Embedded computer vision (advances in pattern recognition), vol 2. Springer London, pp 139–162
294. Vafadar M, Behrad A (2008) Human hand gesture recognition using motion orientation histogram for interaction of handicapped persons with computer. ICISP. LNCS 5099: 378–385
295. Forbes K (2004) Summarizing motion in video sequences. http://thekrf.com/projects/motionsummary/MotionSummary.pdf

296. Tan J, Ishikawa S (2007) High accuracy and real-time recognition of human activities. Annual conference of IEEE industrial electronics society, pp 2377–2382
297. Han J, Bhanu B (2003) Gait energy image representation: comparative performance evaluation on USF HumanID database. Joint international workshop VS-PETS, pp 133–140
298. Han J, Bhanu B (2006) Individual recognition using gait energy image. IEEE Trans Pattern Anal Mach Intell 28(2):133–140
299. Bashir K, Xiang T, Gong S (2008) Feature selection on gait energy image for human identification. IEEE international conference on acoustics, speech and, signal processing, pp 985–988
300. Bashir K, Xiang T, Gong S (2008) Feature selection for gait recognition without subject cooperation. British machine vision conference
301. Yang X, Zhang T, Zhou Y, Yang J (2008) Gabor phase embedding of gait energy image for identity recognition. IEEE international conference on computer and information technology, pp 361–366
302. Chen C, Liang J, Zhao H, Hu H, Tian J (2009) Frame difference energy image for gait recognition with incomplete silhouettes. Pattern Recognit Lett 30(11):977–984
303. Ma Q, Wang S, Nie D, Qiu J (2007) Recognizing humans based on Gait moment image. ACIS international conference on software engineering, artificial intelligence, networking, and parallel/distributed, computing, pp 606–610
304. Yu C, Cheng H, Cheng C, Fan H (2010) Efficient human action and gait analysis using multiresolution motion energy histogram. EURASIP journal on advances in signal processing
305. Ogata T, Tan J, Ishikawa S (2006) High-speed human motion recognition based on a motion history image and an eigenspace. IEICE Trans Inf Syst E89-D(1):281–289
306. Jin T, Leung M, Li L (2004) Temporal human body segmentation. IASTED international conference visualization, imaging, and image processing, pp 1482–7921
307. Singh R, Seth B, Desai U (2006) A real-time framework for vision based human robot interaction. IEEE/RSJ conference on intelligent robots and systems, pp 5831–5836
308. Davis J, Morison A, Woods D (2007) Building adaptive camera models for video surveillance. IEEE workshop on applications of computer vision
309. Ahmad M, Parvin I, Lee S (2010) Silhouette history and energy image information for human movement recognition. J Multimedia 5(1):12–21
310. Watanabe K, Kurita T (2008) Motion recognition by higher orderlocal auto correlation features of motion history images. Bio-inspired, learning and intelligent systems for, security, pp 51–55
311. Chen D, Yan R, Yang J (2007) Activity analysis in privacy-protected video. www.informedia.cs.cmu.edu/documents/T-MM_Privacy_J2c.pdf
312. Ahad A, Tan J, Kim H, Ishikawa S (2010) Action recognition by employing combined directional motion history and energy images. IEEE computer vision and pattern recognition workshop
313. Kindratenko V (1997) Development and application of image analysis techniques for identification and classification of microscopic particles. PhD Thesis, University of Antwerp, Belgium. http://www.ncsa.uiuc.edu/kindr/phd/index.pdf
314. Ahmad M, Hossain M (2008) SEI and SHI representations for human movement recognition. International conference on computer and information technology, pp 521–526
315. Chandrashekhar V, Venkatesh K (2006) Action energy images for reliable human action recognition. Asian symposium on, information display, pp 484–487
316. Chen D, Yang J (2006) Exploiting high dimensional video features using layered Gaussian mixture models. International conference on pattern recognition
317. Meng H, Pears N, Bailey C (2007) A human action recognition system for embedded computer vision application. Workshop on embedded computer vision with computer vision and pattern recognition

318. Meng H, Pears N, Bailey C (2006) Human action classification using SVM_2 K classifier on motion features. Multimedia content representation, classification and security. LNCS 4105:458–465
319. Meng H, Pears N, Bailey C (2007) Motion information combination for fast human action recognition. Conference computer vision theory and applications
320. Meng H, Pears N, Bailey C (2006) Recognizing human actions based on motion information and SVM. IEE international conference intelligent, environments, pp 239–245
321. Babu R, Ramakrishnan K (2003) Compressed domain human motion recognition using motion history information. Int Conf Image Proc 2:321–324
322. Pantic M, Patras I, Valstar M (2005) Learning spatio-temporal models of facial expressions. International conference on measuring, behaviour, pp 7–10
323. Babu R, Ramakrishnan K (2004) Recognition of human actions using motion history information extracted from the compressed video. Image Vis Comput 22:597–607
324. Orrite C, Martinez-Contreras F, Herrero E, Ragheb H, Velastin S (2008) Independent viewpoint silhouette-based human action modelling and recognition. Workshop on machine learning for vision-based motion analysis with European conference on computer vision
325. Jain A, Duin R, Mao J (2000) Statistical pattern recognition: a review. IEEE Trans Pattern Anal Mach Intell 22(1):4–37
326. Shan C, Wei Y, Qiu X, Tan T (2004) Gesture recognition using temporal template based trajectories. Int Conf Pattern Recognit 3:954–957
327. Kellokumpu C, Zhao G, Pietikainen M (2008) Texture based description of movements for activity analysis. Conf Comp Vis Theory Appl 2:368–374
328. Albu A, Beugeling T (2007) A three-dimensional spatiotemporal template for interactive human motion analysis. J Multimedia 2(4):45–54
329. Jan T (2004) Neural network based threat assessment for automated visual surveillance. IEEE Jt Conf Neural Netw 2:1309–1312
330. Liu J, Zhang N (2007) Gait history image: a novel temporal template for gait recognition. IEEE international conference Multimedia and Expo, pp 663–666
331. Xiang T, Gong S (2006) Beyond tracking: modelling activity and understanding behaviour. Int J Comp Vis 67(1):21–51
332. Bobick A, Davis J (1996) An appearance-based representation of action. International conference on, pattern recognition, pp 307–312
333. Davis J (1996) Appearance-based motion recognition of human actions. M.I.T. Media lab perceptual computing group technical report 387
334. Essa I, Pentland S (1995) Facial expression recognition using a dynamic model and motion energy. IEEE computer vision and pattern recognition
335. Haritaoglu I, Harwood D, Davis L (2000) W4: real-time surveillance of people and their activities. IEEE Trans Pattern Anal Mach Intell 22(8):809–830
336. Mittal A, Paragois N (2004) Motion-based background subtraction using adaptive kernel density estimation. IEEE computer vision and pattern recognition
337. Kilger M (1992) A shadow handler in a video-based real-time traffic monitoring system. IEEE workshop on applications of computer vision, pp 1060–1066
338. Yang Y, Levine M (1992) The background primal sketch: an approach for tracking moving objects. Mach Vis Appl 5:17–34
339. Wren C, Azarbayejani A, Darrell T, Pentland A (1997) Pfinder: real-time tracking of the human body. IEEE Trans Pattern Anal Mach Intell 19(7):780–785
340. Stauffer C, Grimson W (1999) Adaptive background mixture models for real-time tracking. IEEE Comp Vis Pattern Recognit 2:246–252
341. McKenna S, Jabri S, Duric Z, Wechsler H, Rosenfeld A (2000) Tracking groups of people. Comp Vis Image Underst 80(1):42–56
342. Arseneau S, Cooperstock J (1999) Real-time image segmentation for action recognition. IEEE pacific rim conference on communications, computers and, signal processing, pp 86–89

343. Sun H, Feng T, Tan T (2000) Robust extraction of moving objects from image sequences. Asian conference on computer vision, pp 961–964
344. Elgammal A, Harwood D, David L (2000) Nonparametric background model for background subtraction. European conference on computer vision
345. Collins R, Lipton A, Kanade T et al (2000) A system for video surveillance and monitoring. Carnegie Mellon University, technical report CMU-RI-TR-00-12
346. Wang C, Brandstein M (1998) A hybrid real-time face tracking system. International conference on acoustics, speech, and signal processing
347. Lipton A, Fujiyoshi H, Patil R (1998) Moving target classification and tracking from real-time video. IEEE workshop on applications of computer vision, pp 8–14
348. Anderson C, Bert P, Wal G (1985) Change detection and tracking using pyramids transformation techniques. SPIE-Intell Robots Comp Vis 579:72–78
349. Bergen J, Burt P, Hingorani R, Peleg S (1992) A three frame algorithm for estimating two-component image motion. IEEE Trans Pattern Anal Mach Intell 14(9):886–896
350. Kameda Y, Minoh M (1996) A human motion estimation method using3-successive video frames. International conference on virtual systems and multimedia
351. Beauchemin S, Barron J (1995) The computation of optical flow. ACM Comput Surv 27(3):443–467
352. McCane B, Novins K, Crannitch D, Galvin B (2001) On benchmarking optical flow. Comp Vis Image Underst 84:126–143
353. Horn B, Schunck B (1981) Determining optical flow. Artif Intell 17:185–203
354. Papenberg N, Bruhn A, Brox T, Didas S, Weickert J (2006) Highly accurate optic flow computation with theoretically justified warping. Int J Comp Vis 67(2):141–158
355. Wixson L (2000) Detecting salient motion by accumulating directionally-consistent flow. IEEE Trans Pattern Anal Mach Intell 22(8):774–780
356. Talukder A, Goldberg S, Matthies L, Ansar A (2003) Real-time detection of moving objects in a dynamic scene from moving robotic vehicles. IEEE/RSJ international conference on intelligent robots and systems, pp 1308–1313
357. Bimbo A, Nesi P (1993) Real-time optical flow estimation. Int Conf Syst Eng Serv Hum Syst Man Cybern 3:13–19
358. Wei J, Harle N (1997) Use of temporal redundancy of motion vectors for the increase of optical flow calculation speed as a contribution to real-time robot vision. IEEE TENCON, pp 677–680
359. Christmas W (1998) Spatial filtering requirements for gradient-based optical flow. British machine vision conference, pp 185–194
360. Rosales R, Sclaroff S (1999) 3D trajectory recovery for tracking multiple objects and trajectory guided recognition of actions. IEEE Comp Vis Pattern Recognit 2:117–123
361. Zou X, Bhanu B (2006) Human activity classification based on gait energy image and co-evolutionary genetic programming. Int Conf Pattern Recognit 3:555–559
362. Ahmad M, Lee S (2008) Recognizing human actions based on silhouette energy image and global motion description. IEEE automatic face and gesture recognition, pp 523–588
363. Inamura T, Toshima I, Tanie H, Nakamura Y (2004) Embodied symbol emergence based on mimesis theory. Int J Robotics Res 23(4–5):363–377
364. Takano W, Yamane K, Sugihara T, Yamamoto K, Nakamura Y (2006) Primitive communication based on motion recognition and generation with hierarchical mimesis model. International conference on robotics and automation, pp 3602–3608
365. Takano W, Nakamura Y (2006) Humanoid robot's autonomous acquisition of proto-symbols through motion segmentation. IEEE-RAS conference humanoid, robotics pp 425–431
366. Kim T, Park S, Shin S (2003) Rhythmic-motion synthesis based on motion-beat analysis. ACM Trans Graph 22:392–401
367. Shiratori T, Nakazawa A, Ikeuchi K (2004) Detecting dance motion structure through music analysis. IEEE automatic face and gesture recognition, pp 857–862

368. Arikan O, Forsyth D, O'Brien J (2003) Motion synthesis from annotations. ACM Annual Conference Series, Computer Graphics (SIGGRAPH)
369. Bradski G, Davis J (2002) Motion segmentation and pose recognition with motion history gradients. Mach Vis Appl 13(3):174–184
370. Griesbeck C (1996) Introduction to Labanotation. http://user.uni-frankfurt.de/~griesbec/LABANE.html
371. Barbic J, Safonova A, Pan J, Faloutsos C, Hodgins J, Pollard N (2004) Segmenting motion capture data into distinct behaviors. Graphics, interface, pp 185–194
372. Kadone H, Nakamura Y (2006) Segmentation, memorization, recognition and abstraction of humanoid motions based on correlations and associative memory. IEEE-RAS international conference on humanoid robots
373. Peker K, Alatan A, Akansu A (2000) Low-level motion activity features for semantic characterization of video. IEEE conference on Multimedia and Expo, pp 801–804
374. Vitaladevuni S, Kellokumpu V, Davis L (2008) Action recognition using ballistic dynamics. IEEE computer vision and pattern recognition
375. Wang T, Shum H, Xu Y, Zheng N (2001) Unsupervised analysis of human gestures. IEEE pacific rim conference on multimedia, pp 174–181
376. Ihara M, Watanabe N, Nishimura K (1999) A gesture description model based on synthesizing fundamental gestures. IEEE SouthEast conference, pp 47–52
377. Badler N, Costa M, Zhao L, Chi D (2000) To gesture or not to gesture: what is the question? Comp graphics, international, pp 3–9
378. Osaki R, Shimada M, Uehara K (1999) Extraction of primitive motion for human motion recognition. International conference on discovery science, LNCS
379. Mahalingam G, Kambhamettu C (2011) Can discriminative cues aid face recognition across age? IEEE automatic face and gesture recognition
380. Zhang W, Shan S, Qing L, Chen X, Gao W (2009) Are Gabor phases really useless for face recognition? Pattern Anal Appl 12:301–307
381. Guo Y, Zhao G, Chen J, Pietikainen M, Xu Z (2009) A new Gabor phase difference pattern for face and ear recognition. Comp Anal Image Patterns 5702:41–49
382. Perez C, Cament L, Castillo L (2011) Local matching Gabor entropy weighted face recognition. IEEE Autom Face Gesture Recognit
383. Wiskott L, Fellous J, Kruger N, Malsburg C (1997) Face recognition by elastic bunch graph matching. IEEE Trans Pattern Anal Mach Intell 19(7):775–779
384. Liu H (2002) Gabor feature based classification using the enhanced fisher linear discriminant model for face recognition. IEEE Trans Image Proc 11(4):467–476
385. Lei Z, Li S, Chu R, Zhu X (2007) Face recognition with local Gabor textons. International conference on advances in, biometrics pp 49–57
386. Xie S, Shan S, Chen X, Meng X, Gao W (2009) Learned local gabor patterns for face representation and recognition. Signal Proc 89:2333–2344
387. Nguyen H, Bai L, Shen L (2009) Local Gabor binary pattern whitened PCA: a novel approach for face recognition from single image per person. International conference on advances in, biometrics pp 269–278
388. Zou J, Ji Q, Nagy G (2007) A comparative study of local matching approach for face recognition. IEEE Trans Image Proc 16(10):2617–2628
389. Chen Y, De la Torre F (2011) Active conditional models. IEEE automatic face and gesture recognition
390. Leordeanu M, Hebert M (2009) A spectral technique for correspondence problems using pairwise constraints. International conference on computer vision, pp 1482–1489
391. Leordeanu M, Hebert M (2009) Unsupervised learning for graph matching. IEEE computer vision and, pattern recognition, pp 864–871
392. Duchennel O, Bach F, Kweon I, Ponce J (2009) A tensor-based algorithm for high-order graph matching. IEEE computer vision and, pattern recognition, pp 1980–1987

393. Caetano T, McAuley J, Cheng L, Le Q, Smola A (2009) Learning graph matching. IEEE Trans Pattern Anal Mach Intell 31:1048–1058
394. Mikolajczyk K, Tuytelaars T, Schmid C, Zisserman A, Matas J, Schaffalitzky F, Kadir T, Gool L (2005) A comparison of affine region detectors. Int J Comp Vis 65:43–72
395. Zass R, Shashua A (2008) Probabilistic graph and hypergraph matching. IEEE computer vision and pattern recognition
396. Torresani L, Kolmogorov V, Rother C (2008) Feature correspondence via graph matching: models and global optimization. European conference on computer vision, pp 596–609
397. Tola E, Lepetit V, Fua P (2008) A fast local descriptor for dense matching. IEEE computer vision and pattern recognition
398. Ke Y, Sukthankar R (2004) PCA-SIFT: a more distinctive representation for local image descriptors. IEEE computer vision and, pattern recognition, pp 506–513
399. Bay H, Tuytelaars T, Gool L (200) SURF: speeded up robust features. European conference on computer vision, pp 404–417
400. Cootes T, Taylor C, Cooper D, Graham J (1995) Active shape models: their training and application. Comp Vis Image Underst 61:38–59
401. Cootes T, Edwards G, Taylor C (2001) Active appearance models. IEEE Trans Pattern Anal Mach Intell 23:681–685
402. Blanz V, Vetter T (1999) A morphable model for the synthesis of 3D faces. Annual conference on computer graphics and interactive, techniques, pp 187–194
403. Asthana A, Goecke R, Quadrianto N, Gedeon T (2009) Learning-based automatic face annotation for arbitrary poses and expressions from frontal images only. IEEE computer vision and, pattern recognition, pp 1635–1642
404. De la Torre F, Nguyen M (2008) Parameterized kernel principal component analysis: theory and applications to supervised and unsupervised image alignment. IEEE computer vision and pattern recognition
405. Morel J, Yu G (2009) ASIFT—a new framework for fully affine invariant image comparison. SIAM J Image Sci 2:438–469
406. Liu C, Hertzmann A, Popovic Z (2005) Learning physics-based motion style with nonlinear inverse optimization. ACM Trans Graph 24:1071–1081
407. Kohlsdorf D, Starner T, Ashbrook D (2011) MAGIC 2.0: a web tool for false positive prediction and prevention for gesture recognition systems. IEEE automatic face and gesture recognition
408. Ashbrook D, Clawson J, Lyons K, Starner T, Patel N (200) Quickdraw: the impact of mobility and on-body placement on device access time. SIGCHI conference on human factors in, computing systems, pp 219–222
409. Ashbrook D, Starner T (2010) MAGIC: a motion gesture desin tool. CHI, pp 2159–2168
410. Dannenberg A (1989) A gesture based user interface prototyping system. ACM symposium on user interface software and technology
411. Dey A, Hamid R, Beckmann C, Li I, Hsu D (2004) A CAPpella: programming by demonstration of context aware applications. CHI
412. Fails J, Olsen D (2003) A design tool for camera-based interaction. SIGCHI conference on human factors in computing systems
413. Brashear H, Kim J, Lyons K, Starner T, Westeyn T (2007) GART: the gesture and activity recognition toolkit. International conference on human-computer interaction
414. Klemmer S, Sinha A, Chen J, Landay J, Aboobaker N, Wang A (2000) SUEDE: a wizard of oz prototyping tool for speech user interfaces. ACM symposium on user interface software and technology
415. Long A, Landay J, Rowe L (2001) Quill: a gesture design tool for pen-based user interfaces. http://quill.sourceforge.net/
416. Maynes-Aminzade D, Winograd T, Igarashi T (2007) Eyepatch: prototyping camera-based interaction through examples. ACM symposium on user interface software and technology, pp 33–42

417. Akae N, Makihara Y, Yagi Y (2011) The optimal camera arrangement by a performance model for gait recognition. IEEE automatic face and gesture recognition
418. Yu S, Tan D, Tan T (2006) Modelling the effect of view angle variation on appearance-based gait recognition. Conf Comp Vis 1:807–816
419. Makihara Y, Sagawa R, Mukaigawa Y, Echigo T, Yagi Y (2006) Which reference view is effective for gait identification using a view transformation model? IEEE computer society workshop on biometrics
420. Wang Y, Yu S, Wang Y, Tan T (2006) Gait recognition based on fusion of multi-view gait sequences. IAPR international conference on, biometrics, pp 605–611
421. Sugiura K, Makihara Y, Yagi Y (2007) Gait identification based on multi-view observations using omnidirectional camera. Asian conference on computer vision, pp 452–461
422. Mori A, Makihara Y, Yagi Y (2010) Gait recognition using periodbased phase synchronization for low frame-rate videos. International conference on, pattern recognition, pp 2194–2197
423. Mowbray S, Nixon M (2003) Automatic gait recognition via Fourier descriptors of deformable objects. IEEE conference on advanced video and signal based surveillance, pp 566–573
424. Maturana D, Mery D, Soto A (2011) Learning discriminative local binary patterns for face recognition. IEEE automatic face and gesture recognition
425. Mikolajczyk K, Schmid C (2005) Performance evaluation of local descriptors. IEEE Trans Pattern Anal Mach Intell 27(10):1615–1630
426. Liao S, Chung A (2007) Face recognition by using elongated local binary patterns with average maximum distance gradient magnitude. Asian conference on computer vision, pp 672–679
427. Liao S, Zhu X, Lei Z, Zhang L, Li S (2007) Learning multiscale block local binary patterns for face recognition. Advances in, biometrics, pp 828–837
428. Wolf L, Hassner T, Taigman Y (2008) Descriptor based methods in the wild. Real-life images workshop with European conference on computer vision
429. Heikkil M, Pietikinen M, Schmid C (2009) Description of interest regions with local binary patterns. Pattern Recognit 42(3):425–436
430. Xie S, Shan S, Chen X, Gao W (2008) V-LGBP: volume based local gabor binary patterns for face representation and recognition. International conference on pattern recognition
431. Vu N, Caplier A (2010) Face recognition with patterns of oriented edge magnitudes. European conference on computer vision, pp 316–326
432. Park S, Savvides M (2011) The multifactor extension of Grassmann manifolds for face recognition. IEEE automatic face and gesture recognition
433. Li Y, Du Y, Lin X (2005) Kernel-based multifactor analysis for image synthesis and recognition. Int Conf Comp Vis 1:114–119
434. Park S, Savvides M (2007) Individual kernel tensor-subspaces for robust face recognition: a computationally efficient tensor framework without requiring mode factorization. IEEE Trans Syst Man Cybern Cybern 37(5):1156–1166
435. Turk M, Pentland A (1991) Eigenfaces for recognition. J Cogn Neurosci 3:71–86
436. Vasilescu M, Terzopoulos D (2002) Multilinear image analysis for facial recognition. Int Conf Pattern Recognit 1:511–514
437. Vasilescu M, Terzopoulos D (2005) Multilinear independent components analysis. IEEE Comp Vis Pattern Recognit 1:547–553
438. Scholkopf B, Smola A, Muller K (2000) Nonlinear component analysis as a kernel eigenvalue problem. Neural computation, pp 1299–1319
439. O'Hara A, Lui Y, Draper B (2011) Unsupervised learning of human expressions, gestures, and actions. IEEE automatic face and gesture recognition
440. Laptev I (2005) On space-time interest points. Int J Comp Vis 64(2):107–123
441. Rapantzikos K, Avrithis Y, Kollias S (2009) Dense saliency-based spatiotemporal feature points for action recognition. IEEE computer vision and pattern recognition

442. Ponce J, Berg T, Everingham M, Forsyth D, Hebert M, Lazebnik S et al (2006) Dataset issues in object recognition. Toward category-level object recognition. LNCS 4170:29–48
443. Pinto N, DiCarlo J, Cox D (2009) How far can you get with a modern face recognition test set using only simple features? IEEE computer vision and pattern recognition
444. Lv F, Nebatia R (2007) Single view human action recognition using key pose matching and viterbi path searching. IEEE computer vision and pattern recognition
445. Rodriguez M, Ahmed J, Shah M (2008) Action MACH: a spatio-temporal maximum average correlation height filter for action recognition. IEEE computer vision and pattern recognition
446. Yuan C, Li X, Hu W, Wang H (2009) Human action recognition using pyramid vocabulary tree. Asian conference on computer vision
447. Weinland D, Boyer E (2008) Action recognition using exemplar-based embedding. IEEE computer vision and pattern recognition
448. Liu J, Ali S, Shah M (2008) Recognizing human actions using multiple features. IEEE computer vision and pattern recognition
449. Perronnin F (2008) Universal and adapted vocabularies for generic visual categorization. IEEE Trans Pattern Anal Mach Intell 30(7):1243–1256
450. Wang Y, Jiang H, Drew M, Li Z, Mori G (2006) Unsupervised discovery of action classes. IEEE Comp Vis Pattern Recognit
451. Liu J, Shah M (2008) Learning human actions via information maximazation. IEEE computer vision and pattern recognition
452. Fathi A, Mori G (2008) Action recognition by learning mid-level motion features. IEEE computer vision and pattern recognition
453. Jia K, Yeung D (2008) Human action recognition using local spatio-temporal discriminant embedding. IEEE computer vision and pattern recognition
454. Wang L, Suter D (2007) Recognizing human activities from silhouettes: motion subspace and factorial discriminative graphical model. IEEE computer vision and pattern recognition
455. Lucena M, Blanca N, Fuertes J (2010) Human action recognition based on aggregated local motion estimates. Machine vision and applications
456. Brox T, Bruhn A, Papenberg N, Weickert J (2004) High accuracy optical flow estimation based on a theory for warping. European conference on computer vision
457. Bruhn A, Weickert J, Schnorr C (2005) Lucas/Kanade meets Horn/Schunck: combining local and global optic flow methods. Int J Comp Vis 61(3):211–231
458. Farneback C (2003) Two-frame motion estimation based on polynomial expansion. Scandinavian conference on image, analysis, pp 363–370
459. Lucena M, Blanca N, Fuertes J, Marin-Jimenez M (2009) Human action recognition using optical flow accumulated local histograms. IbPRIA, pp 32–39
460. Polana R, Nelson R (1993) Detecting activities. IEEE computer vision and, pattern recognition, pp 2–7
461. Shechtman E, Irani M (2007) Space-time behavior-based correlation or how to tell if two underlying motion fields are similar without computing them? IEEE Trans Pattern Anal Mach Intell 29(11):2045–2056
462. Zelnik-Manor L, Irani M (2001) Event-based analysis of video. IEEE Comp Vis Pattern Recognit 2:123–130
463. Ahmad M, Lee S (2006) HMM-based human action recognition using multiview image sequences. Int Conf Pattern Recognit
464. Babu R, Anantharaman B, Ramakrishnan K, Srinivasan S (2002) Compressed domain action classification using HMM. Pattern Recognit Lett 23(10):1203–1213
465. Brand M, Oliver N, Pentland A (1997) Coupled hidden Markov models for complex action recognition. IEEE computer vision and pattern recognition
466. Cuntoor N, Yegnanarayana B, Chellappa R (2005) Interpretation of state sequences in HMM for activity representation. IEEE ICASSP

467. Mendoza M, Perez de la Blanca N (2007) HMM-based action recognition using contour histograms. Iberian conference on pattern recognition and image analysis
468. Morency L, Quattoni A, Darrell T (2007) Latent-dynamic discriminative models for continuous gesture recognition. M.I.T., technical report
469. Wang S, Quattoni A, Morency L, Demirdjian D, Darrel T (2006) Hidden conditional random fields for gesture recognition. IEEE computer vision and pattern recognition
470. Yamato J, Ohya J, Ishii K (1992) Recognizing human action in time sequential images using hidden Markov model. IEEE computer vision and pattern recognition
471. Mikolajczyk K, Uemura H (2008) Action recognition with motion appearance vocabulary forest. IEEE computer vision and pattern recognition
472. Schindler K, Gool L (2008) Action snippets: how many frames does human action recognition require. IEEE computer vision and pattern recognition
473. Wong S, Cipolla R (2007) Extracting spatiotemporal interest points using global information. International conference on computer vision
474. Kienzle W, Scholkopf B, Wichmann F, Franz M (2007) How to find interesting locations in video: a spatiotemporal interest point detector learned from human eye movements. DAGM Symposium, pp 405–414
475. Bay H, Ess A, Tuytelaars T, Gool L (2008) Speeded-up robust features (SURF). Comp Vis Image Underst 110(3):346–359
476. Kameda Y, Ohta Y (2010) Image retrieval of first-person vision for pedestrian navigation in urban area. International conference on pattern recognition
477. Lindeberg T (1998) Feature detection with automatic scale selection. Int J Comp Vis 30(2):79–116
478. Ehsan S, McDonald-Maier K (2009) Exploring integral image word length reduction techniques for SURF detector. International conference on computer and, electrical engineering, pp 635–639
479. Schweiger F, Zeisl B, Georgel P, Schroth G, Steinbach E, Navab N (2009) Maximum detector response markers for SIFT and SURF. Vision, modeling and visualization workshop
480. BenAbdelkader C, Cutler R, Davis L (2002) Motion-based recognition of people in eigengait space. IEEE automatic face and gesture recognition, pp 378–384
481. Fihl P, Moeslund T (2008) Invariant gait continuum based on the duty-factor. Signal, image and video processing, Springer, London
482. Masoud O, Papanikolopoulos N (2003) A method for human action recognition. Image Vis Comput 21(8):729–743
483. Lee L, Grimson W (2002) Gait analysis for recognition and classification. IEEE automatic face and gesture recognition
484. Zhang R, Vogler C, Metaxas D (2004) Human gait recognition. IEEE computer vision and pattern recognition workshop
485. Ben-Arie J, Wang Z, Pandit P, Rajaram S (2002) Human activity recognition using multidimensional indexing. IEEE Trans Pattern Anal Mach Intell 24(8):1091–1104
486. Rahman M, Ishikawa S (2005) Human motion recognition using an eigenspace. Pattern Recognit Lett 26:687–697
487. Wang L, Tan T, Ning H, Hu W (2003) Silhouette analysis-based gait recognition for human identification. IEEE Trans Pattern Anal Mach Intell 25(12):505–1518
488. Liu Z, Sarkar S (2007) Outdoor recognition at a distance by fusing gait and face. Image Vis Comput 6:817–832
489. Boulgouris V, Plataniotis K, Hatzinakos D (2006) Gait recognition using linear time normalization. Pattern Recognit 39(5):969–979
490. Foster J, Nixon M, Bennett A (2003) Automatic gait recognition using area-based metrics. Pattern Recognit Lett 24(14):2489–2497
491. Andrade E, Fisher R, Blunsden S (2006) Detection of emergency events in crowded scenes. IEE international symposium on imaging for crime detection and, prevention, pp 528–533

492. Bobick A, Davis J (2001) The recognition of human movement using temporal templates. IEEE Trans Pattern Anal Mach Intell 23(3):257–267
493. Efros A, Berg A, Mori G, Malik J (2003) Recognizing action at a distance. International conference on computer vision, pp 726–733
494. Gavrila D (1999) The visual analysis of human movement: a survey. Comp Vis Image Underst 73(1):82–98
495. Grimson W, Stauffer C, Romano R, Lee L (1998) Using adaptive tracking to classify and monitor activities in a site. IEEE computer vision and, pattern recognition, pp 22–29
496. Hu M (1962) Visual pattern recognition by moment invariants. IRE Trans Inf Theory 8(2):179–187
497. Iwai Y, Hata T, Yachida M (1998) Gesture recognition from image motion based on subspace method and HMM. Asian Conf Comp Vis 2:639–646
498. Ke Y, Sukthankar R, Hebert M (2005) Efficient visual event detection using volumetric features. International conference on computer vision, pp 166–173
499. Micilotta A, Ong E, Bowden R (2005) Detection and tracking of humans by probabilistic body part assembly. British machine vision conference, pp 429–438
500. Mitchelson J, Hilton A (2003) Simultaneous pose estimation of multiple people using multiple-view cues with hierarchical sampling. British machine vision conference
501. Robertson N, Reid I (2005) Behaviour understanding in video: a combined method. International conference on computer vision, pp 808–815
502. Roh M, Shin H, Lee S, Lee S (2006) Volume motion template for view-invariant gesture recognition. International conference on, pattern recognition, pp 1229–1232
503. Weinland D, Ronfard R, Boyer E (2005) Motion history volumes for free viewpoint action recognition. IEEE international workshop on modeling people and human interaction
504. Zivkovic Z, Heijden F, Petkovic M, Jonker W (2001) Image processing and feature extraction for recognizing strokes in tennis game videos. Annual conference of the advanced school for computing and, imaging, pp 262–267
505. Aggarwal J, Cai Q (1999) Human motion analysis: a review. Comp Vis Image Underst 73:428–440
506. Aggarwal J, Cai Q (1997) Human motion analysis: a review. IEEE nonrigid and articulated motion, workshop, pp 90–102
507. Bobick A, Intille S, Davis J, Baird F, Pinhanez C, Campbell L et al. (1999) The Kidsroom: a perceptually-based interactive and immersive story environment. Presence Teleoperators Virtual Environ 8:367–391
508. Borshukov G, Bozdagi G, Altunbasak Y, Tekalp A (1997) Motion segmentation by multistage affine classification. IEEE Trans Image Proc 6(11):1591–1594
509. Canton-Ferrer C, Casas J, Pardas M (2006) Human model and motion based 3D action recognition in multiple view scenarios. 14th European signal processing conference
510. Cedras C, Shah M (1995) Motion-based recognition: a survey. Image Vis Comput 13:129–154
511. Davis J (2001) Hierarchical motion history images for recognizing human motion. IEEE workshop on detection and recognition of events in Video, pp 39–46
512. Davis J, Bradski G (1999) Real-time motion template gradients using Intel CVLib. International conference on computer vision workshop on frame-rate vision, pp 1–20
513. Davis J, Bobick A (1998) Virtual PAT: a virtual personal aerobics trainer. Perceptual user, interfaces, pp 13–18
514. Davis J, Bobick A (1997) The representation and recognition of action using temporal templates. IEEE computer vision and, pattern recognition, pp 928–934
515. Gao J, Collins R, Hauptmann A, Wactlar H (2004) Articulated motion modeling for activity analysis. International conference on image and video retrieval, workshop on articulated and nonrigid motion
516. Gheissari N, Bab-Hadiashar A (2003) Motion analysis: model selection and motion segmentation. International conference on image analysis and processing, pp 442–447

517. http://gaijin-in-japan.com/2007/08/11/rajio-taiso-radio-exercise/
518. Hu M (1961) Pattern recognition by moment invariants. IRE 49:1218
519. Kahol K, Tripathi P, Panchanathan P, Rikakis T (2003) Gesture segmentation in complex motion sequences. International conference on image processing, pp 105–108
520. Kahol K, Tripathi P, Panchanathan P (2006) Documenting motion sequences with a personalized annotation system. IEEE J Multimedia 13(1):37–45
521. Kahol K, Tripathi P, Panchanathan P (2004) Automated gesture segmentation from dance sequences. IEEE automatic face and gesture recognitionm, pp 883–888
522. Khotanzad A, Hong Y (1990) Invariant image recognition by Zernike moments. IEEE Trans Pattern Anal Mach Intell 12(5):489–497
523. Li L, Zeng Q, Jiang Y, Xia H (2006) Spatio-temporal motion segmentation and tracking under realistic condition. International symposium on systems and control in aerospace and astronautics, pp 229–232
524. Lo C, Don H (1990) Pattern recognition using 3-D moments. Int Conf Pattern Recognit 1:540–544
525. Mangin J, Poupon F, Duchesnay E, Riviere D et al (2004) Brain morphometry using 3D moments invariants. Med Image Anal 8(3):187–196
526. Rosales R (1998) Recognition of human action using moment-based features. Boston University. Tech Rep 98–020:1–19
527. Shen D, Ip H (1999) Discriminative wavelet shape descriptors for recognition of 2-D patterns. Pattern Recognit 32:151–165
528. Son D, Dinh T, Nam V, Hanh T, Lam H (2005) Detection and localization of road area in traffic video sequences using motion information and Fuzzy-Shadowed sets. IEEE international symposium on multimedia, pp 725–732
529. Teh C, Chin R (1988) On image analysis by the methods of moments. IEEE Trans Pattern Anal Mach Intell 10:496–513
530. Valstar M, Pantic M, Patras I (2004) Motion history for facial action detection in video. Int Conf SMC 1:635–640
531. Weinland D, Ronfard R, Boyer E (2006) Free viewpoint action recognition using motion history volumes. Comp Vis Image Underst 104(2–3):249–257
532. Yau W, Kumar D, Arjunan S, Kumar S (2006) Visual speech recognition using image moments and multiresolution Wavelet. International conference on computer graphics, imaging and visualization, pp 194–199
533. Yau W, Kumar D, Arjunan S (2006) Voiceless speech recognition using dynamic visual speech features. HCSNet workshop use of vision in HCI, pp 39–101
534. Yin Z, Collins R (2006) Moving object localization in thermal imagery by forward-backward MHI. Workshop on object tracking and classification, pp 133–140
535. Yuan C, Medioni G, Kang J, Cohen I (2007) Detecting motion regions in the presence of a strong parallax from a moving camera by multiview geometric constraints. IEEE Trans Pattern Anal Mach Intell 29(9):1627–1641
536. Zhang D, Lu G (2004) Review of shape representation and description techniques. Pattern Recognit 37:1–19
537. Ahad A, Tan J, Kim H, Ishikawa S (2010) A simple approach for low-resolution activity recognition. Int J Comput Vis Biomechanics 3(1):17–24
538. Ahad A, Tan J, Kim H, Ishikawa S (2008) Action recognition with various speeds and timed-DMHI feature vectors. International conference on computer and information technology, pp 213–218
539. Ahad A, Tan J, Kim H, Ishikawa S (2008) Human activity recognition: various paradigms. International conference control, automation and systems, pp 1896–1901
540. Ahad A, Ogata T, Tan J, Kim H, Ishikawa S (2008) Complex motion separation and recognition using directional motion templates. Image analysis—from theory to applications, Research Publishing, Singapore, pp 73–82

541. Ahad A, Uemura H, Tan J, Kim H, Ishikawa S (2008) A simple real-time approach for action separation into action primitives. International workshop on tracking humans for the evaluation of their motion in image sequences with british machine vision conference, pp 69–78
542. Ahad A, Tan J, Kim H, Ishikawa S (2009) Temporal motion recognition and segmentation approach. Int J Imag Syst Technol 19:91–99
543. Ahad A, Tan J, Kim H, Ishikawa S (2010) Analysis of motion self-occlusion problem due to motion overwriting for human activity recognition. J Multimedia 5(1):36–46
544. Ahad A, Tan J, Kim H, Ishikawa S (2008) Solutions to motion self-occlusion problem in human activity analysis. International conference on computer and information technology, pp 201–206
545. Ahad A, Tan J, Kim H, Ishikawa S (2008) Directional motion history templates for low resolution motion recognition. Annual conference of the IEEE industrial electronics society (IECON), pp 1875–1880
546. Sigal L, Black M (2006) HumanEva: Synchronized video and motion capture dataset for evaluation of articulated human motion. Department of Computer Science, Brown University, technical report CS-06-08
547. Moeslund T (1999) Summaries of 107 computer vision-based human motion capture papers. University of Aalborg, technical report LIA 99–01
548. Zhou H, Hu H (2004) A survey-human movement tracking and stroke rehabilitation. Department of Computer Sciences, University of Essex, technical report CSM-420
549. Pavlovic V, Sharma R, Huang T (1997) Visual interpretation of hand gestures for human-computer interaction: a review. IEEE Trans Pattern Anal Mach Intell 19(7):677–695
550. Pantic M, Pentland A, Nijholt A, Hunag T (2006) Human computing and machine understanding of human behavior: a survey. International conference on multimodal interface, pp 239–248
551. Pantic M, Pentland A, Nijholt A, Hunag T (2007) Human computing and machine understanding of human behavior: a survey. Hum Comput LNAI 4451:47–71
552. Marcel S (2002) Gestures for multi-modal interfaces: a review. IDIAP research, report 02–34
553. Tangelder J, Veltkamp R (2004) A survey of content based 3D shape retrieval methods. Shape modeling applications, pp 145–156
554. LaViola J (1999) A survey of hand posture and gesture recognition techniques and technology. Brown University, technical report CS-99-11
555. Jaimes A, Sebe N (2007) Multimodal human-computer interaction: a survey. Comp Vis Image Underst 108(1–2):116–134
556. Varga E, Horvath I, Rusak Z, Broek J (2004) Hand motion processing in applications: a concise survey and analysis of technologies. International design conference
557. Poppe R (2007) Vision-based human motion analysis: an overview. Comp Vis Image Underst 108(1–2):4–18
558. Moeslund T, Hilton A, Kruger V (2006) A survey of advances in vision-based human motion capture and analysis. Comp Vis Image Underst 104:90–126
559. Wang J, Singh S (2003) Video analysis of human dynamics—a survey. Real-Time Imag 9(5):321–346
560. Buxton H (2003) Learning and understanding dynamic scene activity: a review. Image Vis Comput 21(1):125–136
561. Aggarwal J, Park S (2004) Human motion: modeling and recognition of actions and interactions. International symposium on 3D data processing, visualization and transmission, pp 640–647
562. Prati A, Mikic I, Trivedi M, Cucchiara R (2003) Detecting moving shadows: algorithms and evaluation. IEEE Trans Pattern Anal Mach Intell 25(7):918–923
563. Mitra S, Acharya T (2007) Gesture recognition: a survey. IEEE Trans SMC 37(3):311–324
564. Moeslund T, Granum E (2001) A survey of computer vision-based human motion capture. Comp Vis Image Underst 81:231–268

565. Hu W, Tan T, Wang L, Maybank S (2004) A survey on visual surveillance of object motion and behaviors. IEEE Trans SMC Appl Rev 34(3):334–352
566. Boulay B, Bremond F, Thonnat M (2006) Applying 3D human model in a posture recognition system. Pattern Recognit Lett 27:1788–1796
567. Wang L, Hu W, Tan T (2003) Recent developments in human motion analysis. Pattern Recognit 36:585–601
568. Joshi M (2006) Digital image processing—an algorithmic approach. Prentice-Hall, India
569. Teknomo K, Tutorial on normalization methods. http://people.revoledu.com/kardi/tutorial/Similarity/Normalization.html
570. Dubes R (2009) Cluster analysis and related issues. Handbook of pattern recognition and computer vision, 4th edn. World scientific, pp 3–32
571. Davis J, Tyagi A (2006) Minimal-latency human action recognition using reliable-inference. Image Vis Comput 24:455–472
572. Chen H, Chen H, Chen Y, Lee S (2006) Human action recognition using star skeleton. ACM international workshop on video surveillance and sensor, networks, pp 171–174
573. Jin N, Mukhtarian F (2006) A non-parametric HMM learning method for shape dynamics with application to human motion recognition. Int Conf Pattern Recognit 2:29–32
574. Kulic D, Takano W, Nakamura Y (2007) Representability of human motions by Factorial Hidden Markov Models. IEEE/RSJ international conference on intelligent robots and systems, pp 2388–2393
575. Peursum P, Bui H, Venkatesh S, West G (2005) Robust recognition and segmentation of human actions using HMMs with missing observations. EURASIP J Appl Signal Proc 2005(1):2110–2126
576. Song S, Xing T (2003) Recognition of group activities using dynamic probabilistic networks. Int Conf Comp Vis 2:742–749
577. Sminchisescu C, Kanaujia A, Li Z, Metaxas D (2005) Conditional models for contextual human motion recognition. Int Conf Comp Vis 2:1808–1815
578. Nguyen N, Phung D, Venkatesh S, Bui H (2006) Learning and detecting activities from movement trajectories using the Hierarchical Hidden Markov Models. IEEE computer vision and, pattern recognition, pp 955–960
579. Park S, Aggarwal J (2004) Semantic-level understanding of human actions and interactions using event hierarchy. International workshop with IEEE computer vision and, pattern recognition, pp 12–20
580. Ryoo M, Aggarwal J (2006) Recognition of composite human activities through context-free grammar based representation. IEEE computer vision and, pattern recognition, pp 1709–1718
581. Shi Y, Huang Y, Minnen D, Bobick A, Essa I (2004) Propagation networks for recognition of partially ordered sequential action. IEEE computer vision and, pattern recognition, pp 862–869
582. Shi Y, Bobick A, Essa I (2006) Learning temporal sequence model from partially labeled data. IEEE computer vision and, pattern recognition, pp 1631–1638
583. Ahmad M, Lee S (2006) Human action recognition using multi-view image sequences features. IEEE automatic face and gesture recognition, pp 523–528
584. Leo M, D'Orazio T, Gnoni I, Spagnolo P, Distante A (2004) Complex human activity recognition for monitoring wide outdoor environments. International conference on, pattern recognition, pp 913–916
585. Davis J, Gao H (2003) Recognizing human action efforts: an adaptive three-mode PCA framework. International conference on computer vision, pp 1463–1469
586. Troje N (2002) Decomposing biological motion: a framework for analysis and synthesis of human gait patterns. J Vis 2:371–387
587. Davis J, Gao H (2004) Gender recognition from walking movements using adaptive three-mode PCA. IEEE computer vision and pattern recognition workshop

588. Fanti C, Zelnik-Manor L, Perona P (2005) Hybrid models for human motion recognition. IEEE computer vision and, pattern recognition, pp 1166–1173
589. Song Y, Goncalves L, Perona P (2003) Unsupervised learning of human motion. IEEE Trans Pattern Anal Mach Intell 25(7):814–827
590. Parameswaran V, Chellappa R (2005) Human action-recognition using mutual invariants. Comp Vis Image Underst 98(2):295–325
591. Yilmaz A, Shah M (2006) Matching actions in presence of camera motion. Comp Vis Image Underst 104(2):221–231
592. Uemura H, Ishikawa S, Mikolajczyk M (2008) Feature tracking and motion compensation for action recognition. British machine vision conference
593. Bodor R, Jackson B, Masoud O, Papanikolopoulos N (2003) Image-based reconstruction for view-independent human motion recognition. IEEE/RSJ international conference on intelligent robots and systems, pp 1548–1553
594. Rao C, Yilmaz A, Shah M (2002) View-invariant representation and recognition of actions. Int J Comp Vis 50(2):203–226
595. Ali S, Basharat A, Shah M (2007) Chaotic invariants for human action recognition. International conference on computer vision
596. Lai Y, Liao H (2006) Human motion recognition using clay representation of trajectories. International conference on intelligent info hiding and multimedia, signal processing, pp 335–338
597. Dewaele G, Cani M (2003) Interactive global and local deformations for virtual clay. Pacific conference on computer graphics and applications, pp 131–140
598. Zelnik-Manor L, Irani M (2006) Statistical analysis of dynamic actions. IEEE Trans Pattern Anal Mach Intell 28(9):1530–1535
599. Loy G, Sullivan J, Carlsson S (2003) Pose-based clustering in action sequences. IEEE international workshop on higher-level knowledge in 3D modeling and motion, analysis, pp 66–73
600. Gorelick L, Galun M, Sharon E, Brandt A, Basri R (2006) Shape representation and classification using the poisson equation. IEEE Trans Pattern Anal Mach Intell 28(12)
601. Gorelick L, Blank M, Shechtman E, Irani M, Basri R (2007) Actions as space-time shapes. IEEE Trans Pattern Anal Mach Intell 29(12):2247–2253
602. Blank M, Gorelick L, Shechtman E, Irani M, Basri R (2005) Actions as space-time shapes. International conference on computer vision, pp 1395–1402
603. Shechtman E, Irani M (2005) Space-time behavior based correlation. IEEE computer vision and, pattern recognition, pp 405–412
604. Viola P, Jones M, Snow D (2003) Detecting pedestrians using patterns of motion and appearance. International conference on computer vision, pp 734–742
605. Oikonomopoulos A, Patras I, Pantic M (2006) Spatiotemporal salient points for visual recognition of human actions. IEEE Trans SMC 36(3):710–719
606. Laptev I, Lindeberg T (2004) Velocity adaptation of space-time interest points. International conference on pattern recognition
607. Rittscher J, Blake A, Roberts S (2002) Towards the automatic analysis of complex human body motions. Image Vis Comput 20:905–916
608. Yilmaz A, Shah M (2005) Actions sketch: a novel action representation. IEEE computer vision and, pattern recognition, pp 984–989
609. Bobick A, Wilson A (1997) A state-based approach to the representation and recognition of gesture. IEEE Trans Pattern Anal Mach Intell 19(12):1325–1337
610. Dong Q, Wu Y, Hu Z (2006) Gesture recognition using quadratic curves. Asian conference on computer vision, pp 817–825
611. Shin M, Tsap L, Goldgof D (2004) Gesture recognition using Bezier curves for visualization navigation from registered 3-D data. Pattern Recognit 37(5):1011–1024
612. Wang L, Suter D (2006) Informative shape representations for human action recognition. International conference on, pattern recognition, pp 1266–1269

613. Zhong H, Shi J, Visontai M (2004) Detecting unusual activity in video. IEEE computer vision and, pattern recognition, pp 819–826
614. Boiman O, Irani M (2005) Detecting irregularities in images and in video. International conference on computer vision, pp 462–469
615. Xiang T, Gong S (2005) Video behaviour profiling and abnormality detection without manual labelling. International conference on computer vision, pp 1238–1245
616. Cuntoor N, Chellappa R (2007) Epitomic representation of human activities. IEEE computer vision and, pattern recognition, pp 846–853
617. Harris C, Stephens M (1988) A combined corner and edge detector. Alvey vision conference, pp 147–151
618. Lowe D (2004) Distinctive image features from scale-invariant keypoints. Int J Comp Vis 60(2):91–110
619. Lucas B, Kanade T (1981) An iterative image registration technique with an application to stereo vision. International joint conference, artificial intelligence, pp 674–679
620. Dong Q, Wu Y, Hu Z (2009) Pointwise motion image (PMI): a novel motion representation and its applications to abnormality detection and behavior recognition. IEEE Trans Circuits Syst Video Technol 19(3):407–416
621. Cox D, Pinto N (2011) Beyond simple features: a large-scale feature search approach to unconstrained face recognition. IEEE automatic face and gesture recognition
622. Pinto N, Cox D, DiCarlo J (2008) Why is real-world visual object recognition hard. PLoS computational biology
623. Pinto N, DiCarlo J, Cox D (2008) Establishing good benchmarks and baselines for face recognition. European conference on computer vision
624. Pinto N, Doukhan D, DiCarlo J, Cox D (2009) A high-throughput screening approach to discovering good forms of biologically inspired visual representation.PLoS computational biology
625. Shreve M, Godavarthy S, Goldgof D, Sarkar S (2011) Macro- and micro-expression spotting in long videos using spatio-temporal strain. IEEE Autom Face Gesture Recognit
626. Ekman P (2001) Telling lies: clues to deceit in the marketplace, politics, and marriage. W.W, Norton and Company
627. Ekman P, Rolls E, Perrett D, Ellis H (1992) Facial expressions of emotion: an old controversy and new findings [and discussion]. Philos Trans Biological Sci 335:63–69
628. Luu K, Bui T, Suen C (2011) Kernel spectral regression of perceived age from hybrid facial features. IEEE automatic face and gesture recognition
629. Tan X, Triggs B (2010) Enhanced local texture feature sets for face recognition under difficult lighting conditions. IEEE Trans Image Proc 19(6):1635–1650
630. Ahonen T, Hadid A, Pietikainen M (2004) Face recognition with local binary patterns. European conference on computer vision, pp 469–481
631. Ahonen T, Hadid A, Pietikainen M (2006) Face description with local binary patterns: application to face recognition. IEEE Trans Pattern Anal Mach Intell 28(12):2037–2041
632. Lui Y, Beveridge J (2011) Tangent bundle for human action recognition. IEEE automatic face and gesture recognition
633. Ben-Yosef G, Ben-Shahar O (2010) Minimum length in the tangent bundle as a model for curve completion. IEEE computer vision and pattern recognition
634. Conway J, Hardin R, Sloane N (1996) Packing lines, planes, etc.: Packings in grassmannian spaces. Exp Math 5(2):139–159
635. Kim T, Cipolla R (2007) Gesture recognition under small sample size. Asian conference on computer vision
636. Kim T, Cipolla R (2009) Canonical correlation analysis of video volume tensors for action categorization and detection. IEEE Trans Pattern Anal Mach Intell 31(8):1415–1428
637. Kovashka A, Grauman K (2010) Learning a hierarchy of discriminative space-time neighborhood features for human action recognition. IEEE computer vision and pattern recognition

638. Laptev I, Marszalek M, Schmid C, Rozenfield B (2008) Learning realistic human actions from movies. IEEE computer vision and pattern recognition
639. Li R, Chellappa R (2010) Aligning spatio-temporal signals on a special manifold. European conference on computer vision
640. Lin Z, Jiang Z, Davis L (2009) Recognizing actions by shape-motion prototype trees. International conference on computer vision
641. Lui Y, Beveridge J, Kirby M (2009) Canonical stiefel quotient and its application to generic face recognition in illumination spaces. IEEE international conference biometrics: theory, applications, and systems, pp 1–8
642. Lui Y, Beveridge J, Kirby M (2010) Action classification on product manifolds. IEEE computer vision and pattern recognition
643. Niebles J, Wang H, Fei-Fei L (2008) Unsupervised learning of human action categories using spatial-temporal words. Int J Comp Vis 79(3):299–318
644. Silva J, Marques J, Lemos J (2005) Non-linear dimension reduction with tangent bundle approximation. ICASSP
645. Veeraraghavan A, Roy-Chowdhury A, Chellappa R (2005) Matching shape sequences in video with applications in human movement analysis. IEEE Trans Pattern Anal Mach Intell 12:1896–1909
646. Wang H, Ullah M, Klaser A, Laptev I, Schmid C (2009) Evaluation of local spatio-temporal features for action recognition. British machine vision conference
647. Edelman A, Arias R, Smith S (1999) The geometry of algorithms with orthogonal constraints. SIAM J Matrix Anal Appl 2:303–353
648. Kendall D (1984) Shape manifolds, procrustean metrics and complex projective spaces. Bull Lond Math Soc 16:81–121
649. Oshin O, Gilbert A, Bowden R (2011) Capturing the relative distribution of features for action recognition. IEEE automatic face and gesture recognition
650. Blake R, Shiffrar M (2007) Perception of human motion. Ann Rev Psychol 58:47–73
651. Schuldt C, Laptev I, Caputo B (2004) Recognizing human actions: a local SVM approach. International conference on pattern recognition
652. Dollar P, Rabaud V, Cottrell G, Belongie S (2005) Behavior recognition via sparse spatio-temporal features. VS-PETS
653. Liu J, Luo J, Shah M (2009) Recognizing realistic actions from videos. IEEE computer vision and pattern recognition
654. Gilbert A, Illingworth J, Bowden R (2009) Fast realistic multi-action recognition using mined dense spatio-temporal features. International conference on computer vision
655. Laptev I, Lindeberg T (2003) Space-time interest points. International conference on computer vision
656. Willems G, Tuytelaars T, Gool L (2008) An efficient dense and scale-invariant spatio-temporal interest point detector. European conference on computer vision
657. Scovanner P, Ali S, Shah M (2007) A 3-dimensional sift descriptor and its application to action recognition. International conference on multimedia, pp 357–360
658. Klaser A, Marszalek M, Schmid C (2008) A spatio-temporal descriptor based on 3D-gradients. British machine vision conference
659. Laptev I, Perez P (2007) Retrieving actions in movies. International conference on computer vision
660. Marszalek M, Laptev I, Schmid C (2009) Actions in context. IEEE computer vision and pattern recognition
661. Ryoo M, Aggarwal J (2009) Spatio-temporal relationship match: video structure comparison for recognition of complex human activities. international conference on computer vision
662. Matikainen P, Herbert M, Sukthankar R (2010) Representing pairwise spatial and temporal relations for action recognition. European conference on computer vision

663. Savarese S, DelPozo A, Niebles J, Fei-Fei L (2008) Spatial-temporal correlatons for unsupervised action classification. WMVC
664. Cui Z, Shan S, Chen X, Zhang L (2011) Sparsely encoded local descriptor for face recognition. IEEE automatic face and gesture recognition
665. Zhao G, Pietikinen M (2006) Local binary pattern descriptors for dynamic texture recognition. International conference on, pattern recognition, pp 211–214
666. Zhang B, Shan S, Chen X, Gao W (2007) Histogram of Gabor phase patterns (HGPP): a novel object representation approach for face recognition. IEEE Trans Image Proc 16(1):57–68
667. Zhang W, Shan S, Gao W, Chen X, Zhang H (2005) Local Gabor binary pattern histogram sequence (LGBPHS): a novel non-statistical model for face representation and recognition. International conference on computer vision
668. Xie S, Shan S, Chen X, Chen J (2010) Fusing local patterns of Gabor magnitude and phase for face recognition. IEEE Trans Image Proc 19(5):1349–1361
669. Bicego M, Lagorio A, Grosso E, Tistarelli M (2006) On the use of SIFT features for face authentication. IEEE computer vision and pattern recognition workshop
670. Albiol A, Monzo D, Martin A, Sastre J, Albiol A (2008) Face recognition using HOG-EBGM. Pattern Recognit Lett 29:1537–1543
671. Gorodnichy D (2005) Associative neural networks as means for low-resolution video-based recognition. International joint conference on neural networks
672. Kong W, Zhang D (2002) Palmprint texture analysis based on low-resolution images for personal authentication. International conference on, pattern recognition, pp 807–810
673. Sobottka K (2000) Analysis of low-resolution range image sequences. PhD Thesis
674. Roh M, Christmas W, Kittler J, Lee S (2006) Robust player gesture spotting and recognition in low-resolution sports video. European conference on computer vision, pp 347–358
675. Lee S, Park J, Lee S (2006) Low resolution face recognition based on support vector data description. Pattern Recognit 39:1809–1812
676. Yanadume S, Mekada Y, Ide I, Murase H (2004) Recognition of very low-resolution characters from motion images captured by a portable digital camera. Advances in multimedia information processing, pp 247–254
677. Nomura M, Yamamoto K, Ohta H, Kato K (2005) A proposal of the effective recognition method for low-resolution characters from motion images. Int Conf Document Anal Recognit 2:720–724
678. Wu H, Chen H, Wu R, Shen D (2006) License plate extraction in low resolution video.International conference on, pattern recognition, pp 824–827
679. Bo N, Dailey M, Uyyanonvara B (2007) Robust hand tracking in low-resolution video sequences. IASTED international conference on advances in computer, science and technology, pp 228–233
680. Roh M, Christmas W, Kittler J, Lee S (2008) Gesture spotting for low-resolution sports video annotation. Pattern Recognit 41(3):1124–1137
681. Jun K, Kunihito K, Kazuhiko Y (1999) Character recognition at low resolution with video camera. J Inst Image Inf Telev Eng 53(6):867–872
682. Cutler R, Davis L (2000) Robust real-time periodic motion detection: analysis and applications. IEEE Trans Pattern Anal Mach Intell 22:781–796
683. Pittermann J, Pittermann A, Minker W (2010) Human emotions. Handling emotions in human-computer dialogues, pp 19–45
684. Kim J, Hill R, Durlach P, Lane H, Forbell E, Core M et al (2009) BiLAT: a game-based environment for practicing negotiation in a cultural context. Int J Artif Intell Educ 19(3):289–308
685. Peursum P, Bui H, Venkatesh S, West G (2004) Human action recognition with an incomplete real-time pose skeleton. Curtin University of Technology, Australia, technical report 2004/1

686. Griffiths P (2001) Emotion and expression. International encyclopedia of the social & behavioral sciences, pp 4433–4437
687. Baillie L, Morton L, Moffat D, Uzor S (2010) Capturing the response of players to a location-based game. Personal and ubiquitous computing
688. Wang N, Marsella S (2006) Introducing EVG: an emotion evoking game. LNCS 4133: 282–291
689. Baillie L, Morton L, Moffat D, Uzor S (2010) An investigation of user responses to specifically designed activities in a multimodal location based game. J Multimodal User Interf 3(3):179–188
690. Albrecht I, Schroder M, Haber J, Seidel H (2005) Mixed feelings: expression of non-basic emotions in a muscle-based talking head. Virtual Real 8:201–212
691. Ekman P, Keltner D (1997) Universal facial expressions of emotion: an old controversy and new findings. Nonverbal communication: where nature meets culture, Lawrence Erlbaum Associates Inc., Mahwah, pp 27–46
692. Wang N, Marsella S, Hawkins T (2008) Individual differences in expressive response: a challenge for ECA design. International joint conference on autonomous agents and multiagent systems
693. Leite I, Martinho C, Pereira A, Paiva A (2008) iCat: an affective game buddy based on anticipatory mechanisms. International conference on autonomous agents and multiagent systems, pp 1229–1232
694. Nguyen Q, Novakowski S, Boyd J, Jacob C, Hushlak G (2006) Motion swarms: video interaction for art in complex environments. ACM international conference multimedia, pp 461–469
695. Peursum P, Bui H, Venkatesh S, West G (2004) Classifying human actions using an incomplete real-time pose skeleton. LNCS 3157:971–972
696. Fujiyoshi H, Lipton A (1999) Real-time human motion analysis by image skeletonization. Workshop on application of computer vision
697. Li W, Zhang Z, Liu Z (2010) Action recognition based on a bag of 3D points. IEEE computer vision and pattern recognition workshop
698. Wang X, Han T, Yan S (2009) An HOG-LBP human detector with partial occlusion handling. International conference on computer vision
699. Canny J (1986) A computational approach to edge detection. IEEE Trans Pattern Anal Mach Intell 8(6):679–698
700. Ahad A, Tan J, Kim H, Ishikawa S (2010) Motion history image: its variants and applications. Mach Vis Appl. doi:10.1007/s00138-010-0298-4
701. Gafurov D (2007) A survey of biometric gait recognition: approaches, security and challenges. NIK conference
702. Tao Y, Grosky W (1999) Object-based image retrieval using point feature maps. International conference on database semantics, pp 59–73
703. Shahabi C, Safar M (2006) An experimental study of alternative shape-based image retrieval techniques. Multimedia Tools Appl. doi:10.1007/s11042-006-0070-y
704. Samma A, Salam R (2009) Enhancement of shape description and representation by slope. World academy of science, engineering and technology, p 59
705. Blostein S, Huang T (1991) Detecting small, moving objects in image sequences using sequential hypothesis testing. IEEE Trans Signal Proc 39(7):1611–1629
706. Meir R, Ratsch G (2003) An introduction to boosting and leveraging. Adv Lectures Mach Learn 2600:119–184
707. Freund Y (1990) Boosting a weak learning algorithm by majority. Workshop on computational learning theory
708. Wang H (2011) Structural two-dimensional principal component analysis for image recognition. Mach Vis Appl 22:433–438
709. Ahad MAR (2011) Computer vision and action recognition, Atlantis Press

710. Thi T, Cheng L, Zhang J, Wang L (2010) Implicit motion-shape model: a generic approach for action matching. In: Proceedings of IEEE international conference on image processing
711. Tian Y, Cao L, Liu Z, Zhang Z (2011) Hierarchical filtered motion for action recognition in crowded videos IEEE transactions on systems, Man, and Cybernetics—Part C
712. Akyol S, Alvarado P (2001) Finding relevant image content for mobile sign language recognition. In: Proceedings of the IASTED international conference signal processing, pattern recognition and applications, pp 48–52
713. Tanawongsuwan R, Stoytchev A, Essa I (1999) Robust tracking of people by a mobile robotic agent, technical report, Georgia Institute of Technology. http://smartech.gatech.edu/handle/1853/3386
714. Brown D, Ghaziasgar M, Connan J (2012) Automated suspicious activity detection. In: Proceedings of Southern Africa telecommunication networks and applications conference (SATNAC)
715. Briassouli A, Kompatsiaris I (2009) Robust temporal activity templates using higher order statistics, IEEE Trans Image proc 18(12)
716. Alvarez L, Esclarín J, Lefébure M, Sánchez J (1999) A PDE model for computing the optical flow. In Proceeding XVI Congreso de Ecuaciones Diferenciales y Aplicaciones, Las Palmas de Gran Canaria, Spain, pp 1349–1356
717. Aubert G, Deriche R, Kornprobst P (1999) Computing optical flow via variational techniques. SIAM J Appl Math 60(1):156–182
718. Black MJ, Anandan P (1991) Robust dynamic motion estimation over time. In: Proceedings 1991 IEEE computer society conference on computer vision and pattern recognition. IEEE Computer Society Press, Maui, pp 292–302
719. Cohen I (1993) Nonlinear variational method for optical flow computation. In: Proceedings eighth scandinavian conference on image analysis, vol 1. Tromsø, Norway, pp 523–530
720. Deriche R, Kornprobst P, Aubert G (1995) Optical-flow estimation while preserving its discontinuities: a variational approach. In: Proceedings second asian conference on computer vision, vol 2. Singapore, pp 290–295
721. Heitz F, Bouthemy P (1993) Multimodal estimation of discontinuous optical flow using Markov random fields. IEEE Trans Pattern Anal Mach Intell 15(12):1217–1232
722. Kumar A, Tannenbaum AR, Balas GJ (1996) Optic flow: a curve evolution approach. IEEE Trans Image Proc 5(4):598–610
723. Nagel H–H (1983) Constraints for the estimation of displacement vector fields from image sequences. In: Proceedings eighth international joint conference on artificial intelligence, vol 2. Karlsruhe, West Germany, pp 945–951
724. Nesi P (1993) Variational approach to optical flow estimation managing discontinuities. Image Vis Comput 11(7):419–439
725. Proesmans M et al (1994) Determination of optical flow and its discontinuities using non-linear diffusion. In Computer vision–ECCV'94, Eklundh J-O (ed) Lecture notes in computer science, vol 801. Springer, Berlin, pp 295–304
726. Schnörr C (1994) Segmentation of visual motion by minimizing convex non-quadratic functionals. In: Proceedings twelfth international conference on pattern recognition, vol A. Jerusalem, Israel, IEEE Computer Society Press, pp 661–663
727. Weickert J, Schnörr C (2001) Variational optic flow computation with a spatio-temporal smoothness constraint. J Math Imag Vis 14(3):245–255
728. Farnebäck G (2001) Very high accuracy velocity estimation using orientation tensors, parametric motion, and simultaneous segmentation of the motion field. In: Proceeding eighth international conference on computer vision, vol 1. IEEE Computer Society Press, Vancouver, Canada, pp 171–177
729. Mémin E, Pérez P (2002) Hierarchical estimation and segmentation of dense motion fields. Int J Comp Vis 46(2):129–155

730. Cremers D (2003) A multiphase levelset framework for variational motion segmentation. In: GriffinLD, Lillholm M (ed) Scale space methods in computer vision, Lecture notes in computer science, vol 2695. Springer, Berlin, pp 599–614
731. Black MJ, Jepson A (1996) Estimating optical flow in segmented images using variable-order parametric models with local deformations. IEEE Trans Pattern Anal Mach Intell 18(10):972–986
732. Anandan P (1989) A computational framework and an algorithm for the measurement of visual motion. Int J Comp Vis 2:283–310
733. Mémin E, Pérez P (1998) A multigrid approach for hierarchical motion estimation. In: Proceedings sixth international conference on computer vision. Narosa Publishing House, Bombay, India, pp 933–938
734. Nagel H-H, Enkelmann W (1986) An investigation of smoothness constraints for the estimation of displacement vector fields from image sequences. IEEE Trans Pattern Anal Mach Intell 8:565–593
735. Alvarez L, Weickert J, Sánchez J (2000) Reliable estimation of dense optical flow fields with large displacements. Int J Comp Vis 39(1):41–56
736. Nagel H-H (1990) Extending the oriented smoothness constraint into the temporal domain and the estimation of derivatives of optical flow. In: Faugeras O (ed) Computer vision, Lecture notes in computer science, vol 427. Springer, Berlin, 139–148
737. Murray DW, Buxton BF (1987) Scene segmentation from visual motion using global optimization. IEEE Trans Pattern Anal Mach Intell 9(2):220–228
738. Elad M, Feuer A (1998) Recursive optical flow estimation–adaptive filtering approach. J Vis Commun Image Represent 9(2):119–138
739. Chiu WY, Tsai DM (2010) A macro-observation scheme for abnormal event detection in daily-life video sequences. EURASIP J Adv Signal Proc. http://dl.acm.org/citation.cfm?id=1928533
740. http://marathon.csee.usf.edu/GaitBaseline/
741. http://www.cse.ohio-state.edu/~jwdavis/CVL/Research/MHI/mhi.html
742. http://www-staff.it.uts.edu.au/~massimo/BackgroundSubtractionReview-Piccardi.pdf
743. Liu J, Shah M, Kuipers B, Savarese S (2011) Cross-view action recognition via view knowledge transfer. In: Proceedings of IEEE conference CVPR