IJCTA, 9(21), 2016, pp. 251-257

Recent Trends in Human Motion Recognition : A Survey

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Abstract **:** Visual analysis of motion for detecting and understanding human activity from image sequences finds the wide range in the field of research. The most important feature of computer vision based analysis is human motion recognition. Human motion analysis includes study of human behavior in contrast to motion features. This paper addresses the survey on advancements in human motion recognition techniques following the survey of previous papers. Several methodologies are used to generalize the human movement which emphases on issues in order to outcome the efficient results with respect to real time, large motions, multiple actions, occlusion and many other for human activity understanding. The paper demonstrates the recent trends in human motion analysis, with problems for future research, which concerns towards fast and accurate representation of motion from the image sequence.

Keywords : Computer Vision, Motion Segmentation, Templates, Optical Flow, Background Subtraction, Histograms.

1. INTRODUCTION

The present scenario is the breath to researchers and provide platform for the dynamic research in computer vision. The first rate feature of computer vision is the analysis and processing of image by understanding images [4]. The explisible quality that makes it efficient for research is the use of high dimensional data, in order to generate image information. Computer vision also describes the transformation of visual images to the image data for vision perception. Various application ranges of computer vision are: controlling process, navigation, detecting events, organizing information, modeling objects, automation inspection and many others [2].The visual analysis of human movement is the foremost application in computer vision. The human movement can be analyzed on the basis of motion analysis, shape analysis, tracking objects, pose recognition etc [1]. The detection based on motion analysis involves segmentation of motion, classification of motion, recognition of activity, and semantic description of motion. In this paper we focus on techniques used for human motion recognition based on motion segmentation. The techniques are based on temporal templates and spatio temporal templates, optical flow, background subtraction, silhouettes, histograms and several others [3], [6], [7], [8], [9]. The survey shows the progress towards understanding of human activity and behavior using various motion based techniques like, MEI, MFH, MHG, GEI, CGI, also uses various Gaussian models, framework estimation, histograms based methods. This paper provides an overview of all the recent approaches used for resolving discriminations and limitations of several techniques. The key purpose of this paper is to review the progress in the field of recognition.

2. LITERATURE SURVEY

The human motion recognition begins with motion segmentation, which focuses on detecting the region of activity in the image sequence. The detection of motion using segmentation method use various approaches for information of the image, this paper mainly focuses on the use of temporal, spatio temporal, optical flow,

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background subtraction and histograms, as described in fig 1. Several other approaches can also be used to segment or classify human actions.

The temporal approaches make use of vector images, where each vector value points the location of the motion in the image [1], [6]. Temporal make use of several methodologies as seen in fig 2 to describe human actions. Aaron F. Bobick et al [1] have presented techniques for motion recognition. They used templates using two components of templates: motion energy image (MEI) and motion history image (MHI) and match with known actions. The temporal approach fails to recognize when an alternate view of the distinct movements was implemented to templates and when two people are in the view field. Further research introduces Motion History Volumes (MHV) [2]. This approach extends motion templates to 3D from 2D to improve the outcomes but,

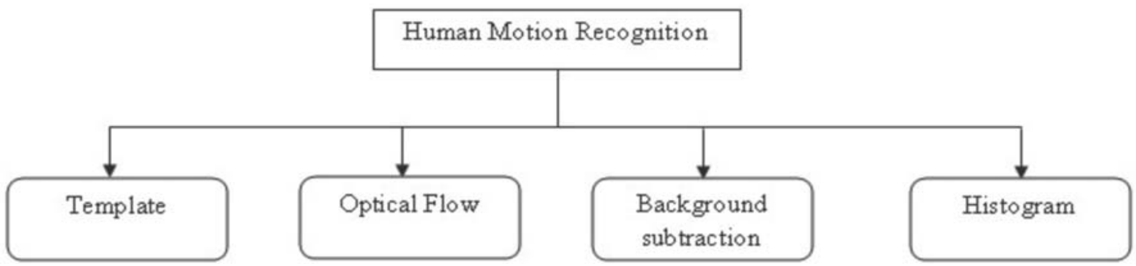

Fig. 1. Method for Motion Recognition Based on Motion Segmentation

further approach may result into improved recognition. In order to resolve the discrimination using temporal, R. venkatesh Babu et al [3] introduces technique using Motion History Image (MHI) along with Motion Flow History (MFH) to describe the information of motion. The technique discriminates the approach when the motion is overlapped. Extension to the work by Md. Atiqur Rahman Ahad et al [4], [5] introduces Directional Motion History Image (DMHI), which develop the basic MHI. They also apply the different datasets with various resolutions and gain faster recognition and solve overlapping of motion. In succession several approaches have been represented which are successfully capable of representing overlapping repetitive actions [6], [7], [8], [9]. To represent the motion using temporal effectively, the Motion History Image combines with Motion Energy Image [10], [11] and gives accuracy in recognition. In recent M. N. Al-Berry [12], motivated by Motion History Image introduces a stationary wavelet- based action representation, which have been used to classify variant actions. An extension to multi-action recognition [13] performs joint segmentation and classiûcation in videos. It demands less computation and give accuracy of 85%. Future approaches may increase the accuracy of recognition using temporal.

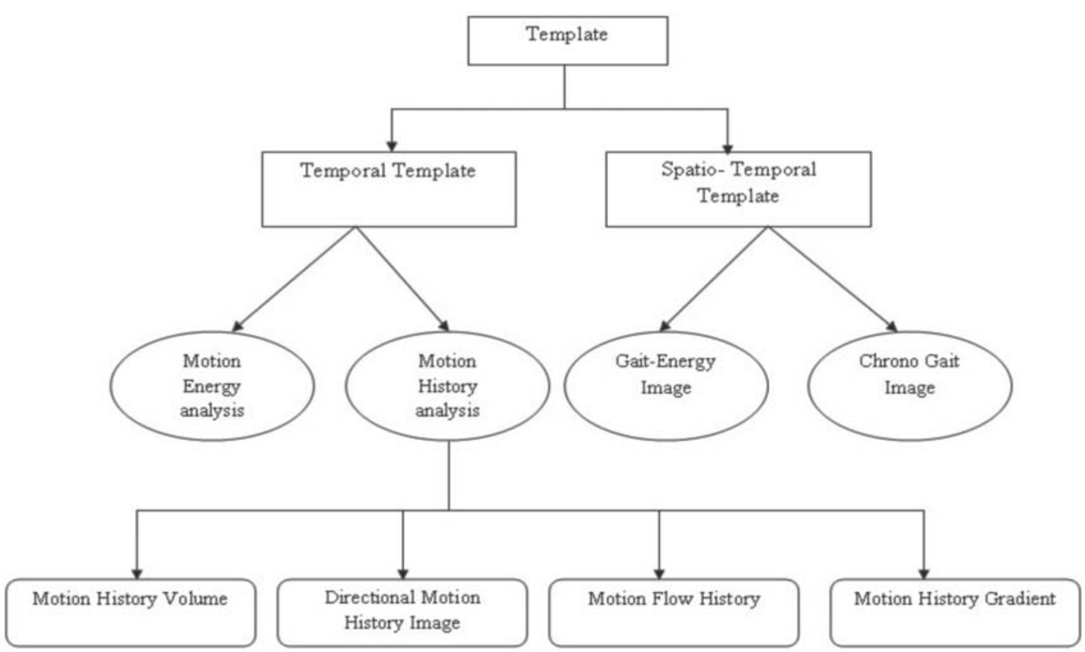

Fig. 2. Template Oriented Techniques.

To enhance the recognition using temporal effectively spatial techniques were represented. In the early researches, a number of techniques using spatial method [14], [15], [16], [17] were introduced, which uses various datasets to approximate the efficient performance. Advancement to the techniques [21] introduces the combination of spatial with temporal [18], which extends the action detection and produces the fine grained pixel level localization results. The Differential Geometric Trajectory Cloud Method (DGTC) [19] transforms early spatial temporal templates, using both large and small scale information. Konstantin's et al [20] proposed a compact local descriptor for spotting actions based on visual space-time measurements, which implements on several applications. For fast and accurate action recognition, the Feature Convariance Matrices [22] method was applied to spatiotemporal. Theextension to this sparse representation gives Spatio-Temporal Laplacian Pyramid Coding descriptor [23], which compares state of art methods with accuracy.

Recognition of motion via temporal give accuracy but in order to obtain high accuracy rate motion can be represented in the form of flow, combing various aspects of motion. The optical flow differentiates the displaced vector pixels from the frame [27]. In previous work, using optical flow techniques they presented framework to recover violation [24], the problem of fast movement of small body parts [25], they integrated the various descriptors to meet the problem and proves to be prominent with the limitations. Enhancement towards the problem of estimation of movements of small size motion. Li Xu et al [26] present a novel optical flow estimation framework, the Extended Coarse to Fine (EC2F) to overcome this issue. Optical flow based segmentation use many background subtraction techniques to gain the prominent results, to obtain the clear background image various Gaussians models [28], [29] were used. Progress in work use optical flow as a feature to show variations in the image, via kernel density estimation [37], non-parametric adaptive density estimation and many others [30], [31], [32], [33], [34].The recent study in the optical flow introduces a baseline algorithm, which states the classical flow [35] of the image information and Rene et al [36]shows an optical ûow model composed of non-local Total Generalized Variation with the proposed scale robust data term, which is able to develop optical ûow accuracy. Fig 3 depicts some of optical flow methods used for recognition.

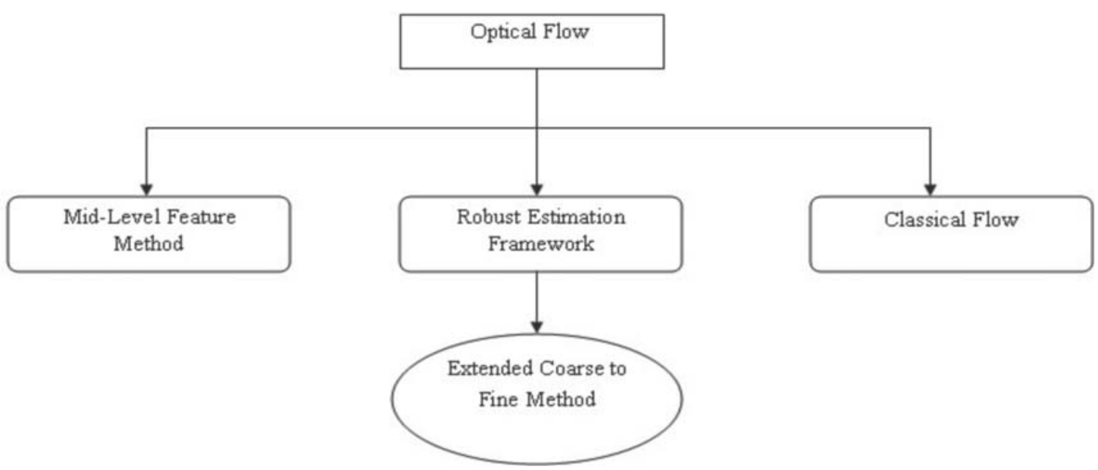

Fig. 3. Optical Flow Oriented Techniques

Representation of motion through histograms is the other way to obtain accuracy in spotting actions. Histograms based human motion recognition involves the plotting of image in the form of pixels, which enables the visual analysis. Histograms make use of several methodologies for recognition as seen in fig 4. While recognizing the motion, the feature sets of image should be clear in order to attain robustness. Navneet dalal et al [38] give the Histograms of Oriented gradient (HOG) descriptor which gives the prominent result for features evaluation of the image. Further work on features evaluation introduces a new method, Integral Histogram [39]. Another approach to the features evaluation was Histograms of Oriented Optical flow (HOOF) [40]. Q. Zhu et al [41] proposed a method for achieving accurate and fast human detection. They combine the cascades of rejectors with the Histograms of Oriented Gradients, which speedup the performance. The recent presentation of The Co-Occurrence HOG [42] founds to be prominent when compared with HOG.

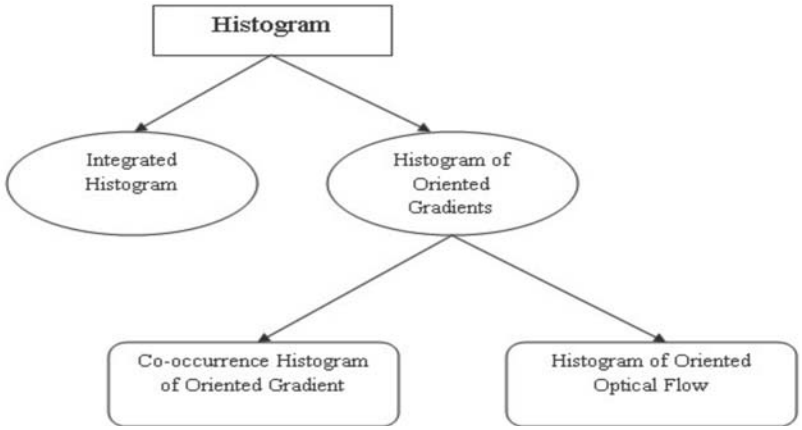

Fig. 4. Histogram Oriented Techniques

Up until several methodologies were presented to step up the recognition but, in recent papers motion is represented by combining the various detection techniques to obtain higher accuracy rate [48]. The survey of combining approach shows that the use of Histogram of Oriented Gradients (HOG) on the Motion History Image (MHI) [43], affects the features via method of temporal normalization and demonstrate the expression dynamics. On combining MHI-HMM [44] improves the problem in detection of motion from temporal. The discriminations in spatio-temporal representations are resolved using Genetic Programming approach [45], the recognition using spatio temporal gives effective outcomes on relating it with optical flow [46]. Hatem A. Rashwan et al [47] computed optical flow model with Histogram Oriented Gradients to achieve robust recognition. Many other combinational techniques [49,50] have been used to improve the accuracy rate, as summarized in table 1. In Future researchers may integrate their work dealing with complex human actions, automatic human detection, occlusion handling, real time optimization and many other approaches that may lead to advancement in the motion recognition with better efficiency.

Table 1. Summarizing recent approaches.

Year	*Approach*	*Key Points*
2014	Supervoxel method and randomized prim 2D object method [46]	Performs hierarchical clustering of super pixels. D RAWBACKS: give undersegmentational error.
2015	Triangulation of image method [49]	Resolves occlusion and recognize large motions
2015	Gradient local auto-correlation technique [51]	Extracts motion features from depth sequences. DRAWBACKS: 0.78% inferior to state of art accuracy and give error on similar actions.
2015	Stochastic modeling of optical flow and gradient [48]	Performs recognition of multiple actions and classification of motion DRAWBACKS: could not separate irrelevant motions.
2015	Differential geometric trajectory cloud algorithm [19]	Differentiate human actions from a large scale information. DRAWBACKS: could not identify complex human actions in full length featured films.
2016	Genetic programming in spatio-temporal representation [45]	Describe motion features and information of high level actions
2016	Fiducial marker system [6]	Resolves the occlusion in action recognition
2016	Probabilistic integration of spatio-temporal fisher vectors [13]	Performs recognition of multiple actions and classification of motion. DRAWBACKS: have less number of freeparameters and less computational.

3. CONCLUSION

Human motion analysis on the basis of computer vision has become important area for the research. Human motion analysis is driven by several promising applications in computer vision such as surveillance, object tracking, motion recognition etc. Recent development in techniques enables the increase in accuracy rate for human recognition. Following the previous work in the field of human recognition, we have presented an overview of recent development in human activity analysis. The key issues described in this paper concerns towards the feature extraction, real time working, resolving occlusion, finding large motions etc. The issues are solved by usingtechniques based on motion segmentation methods, four types of techniques are addressed: temporal differencing, optical flow, background subtraction and histograms method. The recent trend of combining these approaches can successfully resolves the complexity dealing with human activities. We have also mention some discussions regarding future directions in human motion recognition.

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