Hand-Held Object with Action Recognition Based On Convolutional Neural Network in Spatio Temporal Domain

R.Rajitha Jasmine, K.K.Thyagharaajan

Abstract: Several applications such as object recognition and face recognition are established with the progress of smart devices and computer technology, to assist human-computer interaction (HCI). In HCI, Hand-held object recognition has a main role. This approach helps the computer to realise the user's intentions and also meet the user requirements. Hand as an organ which is considered as a direct and natural way of communication for humans. The Hand-held Object Recognition (HHOR) assigns a label for the object which is held in hand this could help machines in understanding the environment and the intention of the people. However, it has not been well studied in the community. So, in this paper, we proposed system for recognizing such activities happening between hands and faces in real time. The interaction events (e.g., eating, phoning and smoking) between hands and faces are analysed using the event analysis approach. Ratio histogram is used for obtaining the essential colour bins for detecting the desired objects via re-projection method. For object tracking and feature extraction, a code book method is used. To recognize various human-object interaction events, the dynamic and multiplicity contexts of events are modelled together. Finally, atwo stage cascaded CNN classifiers for the recognition is implemented as this technology improves the performance of object recognition. To make fair comparisons, six methods were compared in this paper based on the HMDB dataset. This system is effective and can be performed in real time because an exhaustive search process to find possible interaction pairs in the huge space of all possible event parameters is not involved. Experimental results have proved the superiority of our proposed system to analyse different human behaviours and events between hands and a face.

Keywords: Computer technology, Hand-held object, convolutional neural network,

I. INTRODUCTION

In computer vision, Human action recognition is a well-known subject with several vital applications, for example video surveillance and video retrieval. The intention of Human action recognition is to classify the actions in a video automatically. As stated in [1], the performance of action recognition has an impact in the quality of action representations. Recently, Human action recognition in videos has been developed to be a familiar area of investigation owing to its applications in sports analyses, retrieval of video, interaction of human and computer, monitoring of health and video surveillance. In the literature, a lot of papers have been published, each one highlighting a specific attribute of recognition. In [2, 3] many methods for action recognition are accomplished by a single person is focused which classify the entire motion of body by classifying them into spatial and temporal structures. Regarding the human action recognition in [4] a discussion is conducted about multi-view 2D and 3D approaches. For human action recognition in literature [5] several datasets are presented to address several problems like realistic activity recognition, source-based interaction and multi-view analysis.

The techniques for action recognition mostly rely on the descriptors or some of the features extracted for discriminate information for classification. In human action recognition, normally used features/descriptors are histograms oriented gradient (HOG), histograms of optical flow (HOF) [7], bag-of-visual-words (BoVW) [6], motion boundary histograms (MBH) [8], dense trajectories [9] and action bank features [10].

Object recognition is the commonly used technology in HCI and it is considered as a standard task in multimedia and computer vision fields. However, in reality, this task still face many complications due to the impact of some factors such as deformation, illumination, occlusion, etc. For object recognition, certain methods are implemented with the aim to achieve more robust hand-craft feature representation such as SIFT [11], SURF [12], etc.

Recently, there is an emerging growth in Deep Learning (DL) technologies. In 2012 Krizhevsky et al proposed AlexNet [13] which is a classic Convolutional Neural Network (CNN) model. Later, this CNN model becomes the frequently used method for scene and object recognition [14] [15]. In most of the computer vision tasks DL approaches have attained boundless achievements. However, these models use the supervised learning techniques which requires many iterations and a large volume of labelled data to train their huge parameters.

Flexibility of deep learning models are restricted by the description of labelled data towards new classes and limit the applicationsto cope with recently evolving objects or rare types where the annotated images are limited. A method for hand-held object detection have been presented in this paper, moreover several actions (e.g., eating, phoning and smoking) related to hands and faces in reality has been analysed. It is known that, a handheld object diffrerse considerably in its shape, size, textures and colours invariable lighting conditions and viewpoints. For handheld object
detection, we present a ratio histogram to equate the colour variations concerning the frames at the time of interaction process. Then to locate the object of interest a projection technique is used, which extracts the significant colour bins. The Classifier is built using CNN which classifies the hand held objects along with the actions performed. The work flow of this proposed system is illustrated in Fig. 1. In a collection of action videos, the performance of the proposed method is examined to verify its competence in event analysis. This paper’s remaining part is structured as follows. Section 2 presents the related works. Section 3 presents the details on feature extraction. Section 4 presents the Object Tracking using Code Book approach. Section 5 presents the process of Interaction Events representation. Section 5 shows the experimental results. Finally, Section 6 concludes the work.

II. RELATED WORK

A. RGB-D object recognition

Object recognition in computer vision is a standard task. Generally, object recognition using RGB images is a difficult task owing to the variable illumination caused by distressing real-word incidents.

Recent developments of the commodity depth cameras produce a growing volume of visual data that has colour and depth measurements. The depth information improves the performance of object recognition because of its robustness to the depth measurements for light and colour variation. Depth image correcting errors was used by Yuhua Cheng et al [16] in indoor semantic segmentation of images in object classification.

To clearly encode the 3D shape information from depth maps a novel and effective descriptor was proposed by C. Zhang et al [17]. An object detection method in 3D was presented by W. Kehl et al [18] for 6D vote casting that uses reduced descriptors of locally-sampled RGB-D patches. A convolutional auto-encoder was employed for regression which was trained on a huge volume of random local patches. To show the dominance of this approach evaluation was done in three datasets. Besides, object recognition and RGB-D images were used by Xinhang Song et al [19] [20] to improve scene recognition act.

B. Hand-held object recognition

HHO-based studies are categorised into two types i.e. interface of first-person and interface of second-person. Literature in [21] [22] [23] focused on first-person interface. Hand-held object is divided by the Authors in [21] using motion and fuses the object motion and background movement.

Authors in [22] estimated the region of interest for the HHO and the object at distance using laser pointer and head pose estimation.

ROI is found for identifying the HHO along with SIFT. In [23] the study is based on HH0. The data set used by them is CORE50, which has 50 household objects belonging to 10 classes. Using CNN they offer a benchmark for this task. Furthermore, based on second-person interfaces of the works has been done. In which, using RGB-D devices the main task is done, user’s skeletal information is used to detect the position of hand and object segmentation is done by attaining the depth information. RGB, depth image features and 3D point cloud-based hand-craft features are extracted using Fine-tuned AlexNet [26] used by Lv et al [24] [25], finally three types of features are fused and an optimal result is obtained.

III. HAND-HELD OBJECT RECOGNITION

Face detection from videos is done using the Adaboost system [28]. The colour difference of the faces are compared using ratio histogram in the interaction process. For finding the location of the HHO, a re-projection approach is used. For event representation three visual features i.e. the objects size, distance between the object and mouth along with the density of the smog are obtained. Then, each event can be recognised using a two-stage cascaded CNN [40] classifiers. The work flow is presented in Fig. 1. In the recognition phase some of the approaches such as feature extraction, feature fusion and classification are involved. The subsequent sections provides more details about the dissimilar features and the methods used.

![Fig. 1. Proposed Work flow](image)

In the input video, the activities occurring between the face and hands is analysed by extracting the HHO. Identifying the object is a difficult task owing to unknown features such as shapes, sizes, colours, and textures. The HHO can also be detected from the face using the histogram-based approach. In this paper we adopt a AdaBoost-based detector [28] to identify the front and the non-frontal faces. Then the ratio histogram is computed to represent the possible frames in which the HHO appears or disappears.

![Fig. 2. Classification of Action for smoking events](image)

Fig. 2(a) illustrates the classification of action for smoking event. In Fig. 2(b), a frame is shown before smoking i.e. when the cigarette is not present and in Fig. 2(c) the frame in which cigarette appearing is shown. To identify the object (i.e. cigarette) based on frame (b) and (c) the ratio histogram is used. The identified face is denoted as $F$, and the observation captured at time $t$ is denoted as $F_t$. Moreover, $H_i(t)$ is represented as the colour histogram of $F_t$. The ratio histograms of $F_t$ in the forward and backward states at the $r$th order is described below:
\[ \text{Ratio}_{H_i}^{-}(i) = \frac{H_i(i)}{1 + H_i(i)} \quad \text{and} \quad \text{Ratio}_{H_i}^{+}(i) = \frac{H_i(i)}{1 + H_i(i)} \quad (1) \]

From Eq. (1), \( \text{Ratio}_{H_i}^{+} \) power is defined below:

\[ \| \text{Ratio}_{H_i}^{+}(.) \| = \sum_{i=0}^{n_{bin}} \text{Ratio}_{H_i}^{+}(i) \quad (2) \]

The number of colour bins used in \( H_i \) is represented as \( n_{bin} \). The \( \| \text{Ratio}_{H_i}^{+}(.) \| \) will be higher than \( \| \text{Ratio}_{H_i}^{-}(.) \| \) if an object is appeared in \( F_i \). Conversely, \( \| \text{Ratio}_{H_i}^{-}(.) \| \) will be larger if the object disappears in \( F_i \). To conform the appearance or the disappearance of an object in \( F_i \), \( \| \text{Ratio}_{H_i}^{+}(.) \| \) is a helpful factor. The rule in Eqn. 3 will be satisfied, if \( F_i \) contains a new object.

\[ \| \text{Ratio}_{H_i}^{+}(.) \| > \tau_{ratio} \quad (3) \]

The HHO’s position can be located using \( \text{Ratio}_{H_i}^{+} \). In \( \text{Ratio}_{H_i}^{+} \), the average values of all bins is \( T_{Ratio}^{H} \). If \( \text{Ratio}_{H_i}^{+}(i) > 1.5 T_{Ratio}^{H} \) for a colour bin \( i \), then for highlighting the object the colour is a significant colour bin. The re-projection result of important colour bins found from \( \text{Ratio}_{H_i}^{+} \) is illustrated in Fig. 4(c).

Certainly, most of the prominent colours are detected centrally around the cigarette area. Then the location is found using a connected component analysis. The region having maximum area is selected as the object candidate.

**Fig. 3. Identifying the object using colour re-projection approach**

**Fig. 4. Ratio histograms**

The Colour histograms of Fig. 3(a) and (b) is shown in Fig 4(a) and (b) and the Ratio histogram between (a) and (b) is shown in Fig 4(c).

Ratio histogram \( \text{Ratio}_{H_i}^{+} \) between Fig. 4(a) and 4(b) are shown in Fig 3(c). From the training video set the average value of \( \| \text{Ratio}_{H_i}^{+}(.) \| \) calculation is denoted as \( \tau_{ratio} \).

**A. Tracking the Object using Code Book**

The HHO’s trajectory is tracked using a codebook scheme. The particle filters [29] and mean-shift [29] cannot be applied here because of the issues regarding the occlusion of hand and direction of the object.

Using the ratio histogram if a HHO is identified, this system will examine it is recorded in the codebook list not. If sure, its visual features will be recorded and updated into the codebook. If no, it will be added as a new object. For recording the colours, a Gaussian modelling approach is adopted. The object detection is denoted as \( O \) with variance \( (\rho_R, \rho_G, \rho_B) \) and colour means \( (\mu_R, \mu_G, \mu_B) \).

Based on \( O \), the probability of a pixel \( p \) is modelled using the below condition Eqn. 4,

\[ G_{\text{object}}(p) = \exp \left( \frac{(r_p - \mu_R)^2}{\rho_R^2} + \frac{(g_p - \mu_G)^2}{\rho_G^2} + \frac{(b_p - \mu_B)^2}{\rho_B^2} \right) \quad (4) \]

The colour channels of \( p \) are denoted as \( (r_p, g_p, b_p) \). Between two adjacent frames, the visual properties of \( O \) in real cases doesn’t change. Colour is considered as a useful feature for tracking. For every pixel \( p \), whether \( p \) belongs to \( O \) can be determined using Eqn 5.

\[ G_{\text{object}}(p) < 0.85 \quad (5) \]
Later, $I$, will be transformed to a binary map and the position of $O$ will be extracted by applying the connected component analysis. $O$ can be found and tracked when the object listed in the codebook is conformed. Output of tracking the HHO using the proposed approach is illustrated in Fig. 5. After tracking $O$, the distance is found for representing an action.

For a detected face $F_t$ with dimension $w_{F_t} \times h_{F_t}$ and center $(c^x_{F_t}, c^y_{F_t})$, using the Adaboost approach the mouth region can be identified [30]. Though, due to the hands the mouth is always occluded. Hence, to prevent the issues of occlusion and also considering the efficiency, the mouth is expected to be fixed in $F_t$ with the position $(c^x_{F_t}, c^y_{F_t} - h_{F_t}/3)$.

![Fig. 5. Results of Colour slicing based Object tracking. For event representation the distance of object to the mouth is considered as a visual cue.](image)

In Fig. 5, two examples are shown in which the mouth region is represented as blue squares shown in the face.

**B. Smog density estimation**

In this paper, three features are used to represent an interaction event i.e., size of object, distance between hands and the HHO, and the density of smog.

In these, the smog’s visible features are unclear and inexact in texture and shape. Thus, the density of smog is termed “inferior” because compared with the other features it is less reliable in representing an event. As the smog flutters in the air, represented as a moving block. Using the background subtraction or optical flow approach “moving” feature can be extracted. In this approach, background subtraction is done using codebook technique [31]. To calculate the motion of pixels, optical flow is used.

Then, for event analysis the real smog blocks are isolated from the non-smog ones. For the verification task various smog features will be extracted from the HIS colour space. The smog colour is distributed in a specific area after analysing a set of training videos. A pixels edge response is blurred due to the smog.

![Fig. 6. Smog detection results. Blue colour denotes the smog region](image)

In this paper, ten sub-band features are extracted from each moving block using three levels of wavelet decomposition. The results of smog detection are shown in Fig. 6. Bounding boxes $B_{left}$ and $B_{right}$ are set besides the face region $F_t$, to calculate the density of smog.

![Fig. 7. Bounding box settings](image)

Bounding box’s geometry settings are shown in Fig. 7. Both the base of $B_{left}$ and $F_t$ are similar and the boundaries of $B_{right}$ is also set similarly. The pixels of the smog identified within $B_{left}$ and $B_{right}$ is denoted as $n_{smog}$. Then, $\text{den}_{smog}$ (i.e., the density of smog) is described as: $\text{den}_{smog} = n_{smog}/n_{box}$.

Eight action primitives with this density for event analysis is specified in Section 4.

**IV. INTERACTING EVENTS BETWEEN HAND AND FACE**

Visual features are required to analyse the interactive behaviours between faces and hands after each frame is converted into different action primitives. The event representation and the frame coding details are discussed in this section.

**A. Frame Coding**

In event analysis, each frame is converted into a symbol $m_i$ using three bins, weights are added to each bin. The weight for the $k^{th}$ bit is denoted as $W_{bk}$ and $\oplus$ is the X-OR operator.
Fig. 8: Different weights for symbol comparisons

In the above fig. 8 shows different weights for the symbols comparison. We assign 3, 2, 1 as the values of \( W_{b_1}, W_{b_2}, \) and \( W_{b_3}. \) The bit weight \( W_{b_k} \) of the object size is the highest, because than other features it intensely identifies the cigarettes.

The distance between \( m_i \) and \( m_j \) is calculated as follows:

\[
\beta [m_i, m_j] = \sum_{k=0}^{K} W_{b_k} (b_m^w \oplus b_m^w)
\] (6)

Where the \( k^{th} \) bit of the symbol \( m_i \) is denoted as \( b_m^k. \) The smog density’s bit weight \( W_{b_k} \) is easily affected by noise.

B. Event Representation

A set of action primitives used to convert an event to a string is denoted as \( M. \) Observation of an event is denoted as \( O, \) a series of symbols are converted into \( M. \) i.e. \( O = \{A_1, A_2, ..., A_n\}, \) where \( A_i \in M. \) Many repeated actions will be included in an event in a real case. A new symbol \( S_j \) is used to represent \( O, \) which implies the recurrent state where \( S_j \) is the \( j^{th} \) action in \( O \) which is repeated \( r_j \) times, i.e., \( S_j = (A_1, r_1) \) and \( A_i \in M. \) Hence, more efficiently \( O \) can be represented as:

\[
O = \{(A_1, r_1), (A_2, r_2), ..., (A_n, r_n)\} = (A, r)
\] (7)

Where \( A = (A_1, A_2, ..., A_n) \) and \( r = (r_1, r_2, ..., r_n) \).

Eight action primitives generated to encode the above in Table 1. Examples are presented in Fig 9 to clarify the primitive’s m4, m5, and m7.

![Eight action primitives](image)

Table 1. Physical meanings of eight action primitives.

<table>
<thead>
<tr>
<th>Primitives</th>
<th>R</th>
<th>L</th>
<th>S</th>
<th>Meaning</th>
</tr>
</thead>
<tbody>
<tr>
<td>( m_0 )</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>Non-cigarette, leaving, escalating</td>
</tr>
<tr>
<td>( m_4 )</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>Non-cigarette, leaving, declining</td>
</tr>
<tr>
<td>( m_5 )</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>Non-cigarette, approaching, escalating</td>
</tr>
<tr>
<td>( m_6 )</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>Non-cigarette, approaching, declining</td>
</tr>
<tr>
<td>( m_7 )</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>Cigarette, leaving, escalating</td>
</tr>
<tr>
<td>( m_8 )</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>Cigarette, leaving, declining</td>
</tr>
<tr>
<td>( m_9 )</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>Cigarette, approaching, escalating</td>
</tr>
<tr>
<td>( m_{10} )</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>Cigarette, approaching, declining</td>
</tr>
</tbody>
</table>

Eight action primitives’ physical meanings are illustrated above in Table 1. Examples are presented in Fig 9 to clarify the primitive’s m4, m5, and m7.

![Examples](image)

Fig. 9. Visual interpretations of the Primitives m4, m5 and m7. (a) Cigarette, leaving, escalating. (b) Cigarette, leaving, declining. (c) Cigarette, approaching, declining.

V. EVENT RECOGNITION USING TWO CASCADED STAGES CNN CLASSIFIERS

The design of the CNN classifier-1 having 5 layers with weights are shown in Fig 10. The first four layers are the convolutional layers and the last layer is the fully-connected layer. The presence of hand-held object is rapidly verified at this stage, so this classifier is constructed with edge map input. With the similar architecture, the classifier 2 is built. In the training step of CNN, the over fitting problem is common. To deal with this, the dataset is artificially enlarged for CNN training particularly in small dataset. Two distinct forms of data augmentation are done. The first is mirror image, using this the size of the training data gets increased and also reduces over fitting and creates more training samples.

![The architecture of our CNN classifier](image)

Fig. 10. The architecture of our CNN classifier

The second is initiating PCA [39] (Principal Components Analysis) in Alex-Net [32], which uses three quantities to alter the ratio histogram channels intensity. They are defined by:

\[
[E_1, E_2, E_3] = \alpha_1 \lambda_1, \alpha_2 \lambda_2, \alpha_3 \lambda_3
\] (8)

Where \( \lambda_k \) and \( E_k \) are the eigenvalue and the eigenvector of the \( 3 \times 3 \) covariance matrix of histogram values, the random variable are denoted as \( \alpha_k \).

VI. EXPERIMENTAL RESULTS

In this paper, three events such as drinking, phoning and smoking are collected to evaluate the performance of the proposed approach. Twenty actors performed each action certain times in several lighting conditions; as a result, 100 sequences were collected for each event. Other kinds of events can also be analysed by using our proposed scheme. Frame rate set for the system is 15fps. Simulation is conducted in Mat lab (R2014a) on a personal computer, configured with Intel 4720HQ 2.6GHz processor and 8 GB memory. For performance evaluation the first set of experiments are used. The outcome of detecting a cigarette is shown in Fig. 11 which is...
displayed in the open environment. Fig 11b and d shows the detection results from Fig 11 a and c.

![Detection results](image)

**Fig. 11. Detection results of Cigarette.** The original frame is shown in (a) and (c). The ratio histogram based detection results are presented in (b) and (d).

Table 2 lists the accuracy analysis of the detection of phone and cigarette. No tracking technique was used here to make a fair performance evaluation. The number of frames used for testing is 2200. The number of "false-positive" is 32, "true-positive" is 2732 and "false-negative" is 249. Accuracy for detecting cigarettes using the proposed approach is found to be 91.7%.

<table>
<thead>
<tr>
<th>Object</th>
<th>Frames</th>
<th>True positive</th>
<th>False negative</th>
<th>False alarm %</th>
<th>Miss rate</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Can</td>
<td>922</td>
<td>892</td>
<td>40</td>
<td>1.72</td>
<td>0.52</td>
<td>96.2</td>
</tr>
<tr>
<td>Phone</td>
<td>368</td>
<td>324</td>
<td>312</td>
<td>3.55</td>
<td>8.46</td>
<td>88.9</td>
</tr>
<tr>
<td>Cigarette</td>
<td>301</td>
<td>273</td>
<td>248</td>
<td>1.08</td>
<td>9.23</td>
<td>91.7</td>
</tr>
</tbody>
</table>

Because of the hand occlusion caused in the phoning action, the phone is not seen clearly. Therefore, identifying the phone in the front view is not possible compared to the side view. Accuracy for phone detection is 88.9%.

![Detection results](image)

**Fig. 12. Results of phone and can.** (a) (c) and (e) shows the original image. (b) (d) and (f) shows the detected images.

The can which is held in hand is also detected for detecting the drinking events from videos. The results of detecting the can and phone is seen in Fig. 12, the phone is detected in the side view.

![Detection results](image)

**Fig 13(a) Results of smoking event detection, (b) Results of drinking event detection, (c) Results of phoning event detection.**

The results of smoking, drinking and phoning event analysis from YouTube videos is presented in Fig. 13. The experiments done above have confirmed the dominance of proposed approach in HHOR.

<table>
<thead>
<tr>
<th>Approach</th>
<th>Action categories</th>
<th>Smoking (%)</th>
<th>Eating (%)</th>
<th>Drinking (%)</th>
<th>AVG (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>HOG</td>
<td>Smoking</td>
<td>35.49</td>
<td>34.23</td>
<td>34.88</td>
<td>34.87</td>
</tr>
<tr>
<td></td>
<td>Eating</td>
<td>31.65</td>
<td>28.81</td>
<td>29.37</td>
<td>29.94</td>
</tr>
<tr>
<td></td>
<td>Drinking</td>
<td>37.19</td>
<td>34.68</td>
<td>35.85</td>
<td>35.91</td>
</tr>
<tr>
<td>Trajectory</td>
<td>Action bank</td>
<td>34.65</td>
<td>32.23</td>
<td>33.11</td>
<td>33.33</td>
</tr>
<tr>
<td></td>
<td>Trajectory + HOG</td>
<td>41.55</td>
<td>39.43</td>
<td>39.87</td>
<td>40.28</td>
</tr>
<tr>
<td></td>
<td>HOF</td>
<td>38.46</td>
<td>36.35</td>
<td>36.84</td>
<td>37.22</td>
</tr>
<tr>
<td>Our method</td>
<td></td>
<td>43.67</td>
<td>40.21</td>
<td>41.95</td>
<td>41.94</td>
</tr>
</tbody>
</table>

Based on the HMDB [33] dataset, six methods are used for comparison, histogram of optical flow (HOF) [34], histogram of oriented gradients (HOG) [35], dense trajectory, action bank [36], GIST [37], HOF and HOG based dense trajectory.

The collected dataset comprises of human–human communications, facial and general body movements. From the YouTube videos and movies many video clips are collected. Three action categories (i.e. including, smoking, phoning and eating) are selected from the dataset for comparison. Spatial–temporal interest points (STIP) for every clip were initially calculated in HOG and HOF methods, then for action classification their 3D HOGs and HOFs were extracted. Action bank [36], GIST [37], HOF and HOG based dense trajectory.

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VII. CONCLUSIONS

As it is known that a HHO’s can vary considerably in its sizes, shapes, colours, and textures under distinct viewpoints and lighting conditions. The detection task is made very challenging due to the uncertainty. Another challenge along with the uncertainty, is the multiplicity of event representation. In real time, an event is rarely performed with the same, repetitions, beginning states and ending states. The multiplicity of an event can vary significantly in its representation. Number of possible combinations and relative configurations between the analysed object and body parts makes the multiplicity to increase in order to make the interaction event analysis more complicated. Ratio histogram is used in this approach for detecting the object held in hand and it is applied to analyse several actions (e.g. smoking, phoning and eating). The colour difference between frames are compared using the ratio histogram during the interaction process. The object of interest is located using a projection technique by extracting significant colour bins. Three visual features are extracted for event representation i.e. the size of object, the distance concerning mouth and the object held in hand, and the density of smog. To recognize the interaction events between human and object, the dynamic and multiplicity contexts of events are modelled together. CNN classifiers are used to recognise the events. For event analysis, the average accuracy comparisons among different methods on the HMDB dataset is found to be 41.94%. This approach can be performed in real time because it doesn’t have an in-depth search process to find possible interactive pairs in the huge space of all possible event parameters. Our proposed method have been rigorously validated on a considerable event videos to prove its dominance in event analysis from the prospects of efficiency and robustness.

REFERENCES


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