Fast Realistic Multi-Action Recognition using Mined Dense Spatio-temporal Features

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Abstract

Within the field of action recognition, features and descriptors are often engineered to be sparse and invariant to transformation. While sparsity makes the problem tractable, it is not necessarily optimal in terms of class separability and classification. This paper proposes a novel approach that uses very dense corner features that are spatially and temporally grouped in a hierarchical process to produce an overcomplete compound feature set. Frequently reoccurring patterns of features are then found through data mining, designed for use with large data sets. The novel use of the hierarchical classifier allows real time operation while the approach is demonstrated to handle camera motion, scale, human appearance variations, occlusions and background clutter. The performance of classification, outperforms other state-of-the-art action recognition algorithms on the three datasets; KTH, multi-KTH, and real-world movie sequences containing broad actions. Multiple action localisation is performed, though no groundtruth localisation data is required, using only weak supervision of class labels for each training sequence. The real-world movie dataset contain complex realistic actions from movies, the approach outperforms the published accuracy on this dataset and also achieves real time performance.

1. Introduction

Action recognition shares many of the problems associated with object recognition from static images such as the ability to deal with intra class variation, occlusion, scale and background clutter. In the context of object recognition, these problems are generally solved using the bag of words or feature based approaches [26] combined with a state of the art machine learning technique such as a Boosting [25] or Support Vector Machines [21]. However, it has not been proven that this can be directly transferred into the temporal domain, for action recognition, without compromise. Given the quantity of images in a video sequence, the features used

are often engineered to be sparse and fire rarely to reduce overheads. These sparse features are assumed to be the most descriptive for the learnt actions, however, it is possible that the sparsity disregards important discriminatory information.

Building on the success of data mining within other fields [20, 6, 2], we propose to use data mining within the action recognition field to allow a multi stage classifier to be learnt from a large set of simple features. Initially a very localised neighbourhood grouping is used to form compound grouping of features. The neighbourhood is hierarchically increased until the final stage uses only the relative position of groupings to provide scale invariance. The novel hierarchical approach allows for real time operation and out performs other state of the art approaches on the KTH dataset [21]. Finally we present results on two more challenging sequences. Multi-KTH [24] to demonstrate its performance at classifying and localising multiple actions in noisy cluttered scenes containing camera motion and the extremely challenging data of [12] which contains segments extracted from a variety of movies.

2. Related Work

Much of the early work in action recognition was tested on relatively simple single person uniform background sequences [21, 7]. To address this, more natural and diverse video settings are being developed. Laptev *et al* [13] developed a motion model using optical flow [3] [16] to recognise smoking and drinking actions within a feature length film. Uemura *et al* [24] used a motion model based on optical flow combined with SIFT feature correlation in order to accurately classify multiple actions on a moving camera sequence. Laptev *et al* [12] used space time features within a spatio-temporal bag of words model on a large selection of movie film clip actions. While within object recognition, success has been shown by bag of words approaches [20, 14, 23]. The bag of words approach has also been extended to the temporal domain [21, 4, 18, 12]. However to scale to the temporal domain, the occurrence

of the complex feature must be kept sparse. Scovanner *et al* [22] extended the 2D Harris detector and 2D SIFT descriptor [15] into three dimensions, causing the feature to fire far less often. Similarly, Willems *et al* [27] extended the 2D hessian detector and SURF descriptor to the spatio-temporal domain.

Quack *et al* [20] applied *Association rule* data mining to object recognition by mining spatially grouped SIFT descriptors. We have previously applied a similar approach to mining actions from video. This paper extends previous work published by Gilbert *et al* [6]. The previous work focused on single person classification on the simple KTH dataset. This paper extends the technique to multi person detection and localisation, and introduces a hierarchical application of the mining technique which provides a significant performance increase. Furthermore, the hierarchy provides both speed and scalability which allows the real time application of the approach to detecting complex actions in movies.

The main contributions of this paper are the use of a hierarchical classifier to provide a fast accurate multi-action classifier using data mining and the localisation and recognition of simultaneous multiple actions. Our approach outperforms all previously published work on the three datasets that we test upon. The simple features used are explained in section 3, and how they are grouped in the hierarchical classifier in section 4. The training and recognition of the classifier is shown in section 5, results and a conclusion are presented in sections 6 and 7.

3. Features

Space-time features have shown good performance for action recognition [21, 4]. They can provide a compact representation of interest points, with the ability to be invariant to some image transformations. While many are designed to be sparse in occurrence [21, 4, 12], we use dense simple 2D harris corners [8]. In [6] we maintained a relatively simple neighbourhood grouping. Here we increase the detail of the neighbourhood through the hierarchical classifier, this improves the speed and accuracy of the approach dramatically. The features are detected in (x, y) , (x, t) and (y, t) channels in the sequences. This provides information on spatial and temporal image changes but is a far denser detection rate than 3D harris corners [11, 12] and encodes both spatial and spatio-temporal aspects of the data. The overcomplete set of features are then reduced through the levels of mining. The interest points are extracted at multiple levels of spatial scales (σ_i) with $\sigma_i = 3 * 2^{i-1}$, where $i = 1, \dots, 5$. This covers scales of corner interest points from 3x3 up to 48x48 pixels in size. Figure 1 shows the example corner detections on two frames. Figure 1(b) shows the large amount of corner detections on the multi-KTH dataset [24] where there are around 1500 corners detected per frame.

Figure 1. Corner Detection on two Frames, (a) An example of HugPerson from Laptev Movie Dataset [12], (b) Boxing and Handclapping examples from Multi-KTH Dataset [24]

To characterize the motion of the interest points, the dominant orientation of the corners is also recorded. This is quantised into k discrete orientations. In our experiments $k = 8$, therefore the orientation is quantised into $\frac{1}{4}\pi$ bins aligned with the points of a compass. For each interest point detected, it is represented by a 3 digit code $[Scale, Channel, Orientation]$: The scale at which the interest point was detected $Scale = \{1, \dots, 5\}$. The channel the interest point was detected in $Channel = 1, \dots, 3$ with $1 = (x, y)$, $2 = (x, t)$ and $3 = (y, t)$. Finally the dominant orientation of the corner quantised into $\frac{1}{4}\pi$ bins, so $Orientation = \{1, \dots, 8\}$.

4. Neighbourhood Grouping

Given a set of encoded corners, their relationships to other corners are used to build stronger compound features. A hierarchical neighbourhood grouping is proposed, that allows initial stages to identify short localised compound features. Subsequent levels then group these compound features into increasingly higher level spatio-temporal features. The final stage encoding the relative positions of compound features. This hierarchical process is designed to speed up the overall classification and improve accuracy in a similar way to that of a cascaded classifier [5].

4.1. Hierarchical Grouping

The dense corner features are hierarchically grouped into increasingly higher level compound features. This has the advantage of being fast to compute and able to produce more complex features to pass to the successive grouping stages. A regular grid is used to encode spatial information about the local neighbourhood of an interest point. Each neighbourhood is divided into 3x3x3 cuboids with each cuboid ω pixels wide and high. Figure 2 shows an illustration of the process. The grid extends in space and time in order to use the important temporal information concurrently. The cuboids within the grid are labelled sequentially from 0 to 26 and the grid is centered over each interest point in turn. Any other interest points that occur within the grid

neighbourhood have their ID prefixed with the label of the cuboid as shown in Figure 2. After all neighbouring interest

Figure 2. (a) Shows the grid design centered on the interest point marked as a cross, with five local features shown as corners. (b) shows the spatial and temporal encoding applied to each local feature. (c) Concatenating the local features into a transaction vector T for this interest point.

points have been prefix with their specific cuboid label they are concatenated into a 1D vector. This vector of neighbouring interest points is called a *transaction vector*, T , where each of the neighbouring interest points are termed *items*. We are especially interested in learning discriminative configurations, which appear frequently in the specific action sequence, and rarely on other actions or the background. Therefore, for each action class the transaction vectors are appended with a specific action label. For example, the complete transaction for the interest point in Figure 2 is {01221, 08116, 13216, 18116, 21111, *action*}. In order to identify the frequently reoccurring patterns within the transaction vectors, association rule data mining is used. All the transaction vectors from all action training sequences are combined into a single database and fed into a data mining algorithm called APriori [1]. The APriori association rule algorithm is applied to the transaction database, this computationally efficient approach, finds the subsets of the transaction vectors which are frequently occurring in other transaction vectors of the same action class. The resultant subsets are called frequently reoccurring itemsets. The resulting frequent configurations are then used to group the corner features over a larger grid in the next hierarchical stage. For a greater explanation of the apriori data mining approach see the previous work by Gilbert *et al* [6].

5. Action recognition

Equipped with the approach described previously, it is now possible to learn distinctive high level features to describe an action sequence from a very large set of simple 2D corners.

5.1. Training

For action recognition, the simple corner features described in section 3 are densely detected and each feature

is encoded with its three digit value.

For the current work, a two stage hierarchical grouping process is used, the initial stage uses a very localised neighbourhood where the width and height of each neighbourhood tile, ω is 1 pixel, further levels of the hierarchy do not give significant improvement on this data as will be discussed in section 6.4. This first stage of grouping, produces around 7 million transaction vectors. For most clustering methods this would be difficult to use, however with the association rule mining it takes around 1 minute to compute the frequent configurations M^1 , of the corners.

The second and final stage of grouping uses a slightly different grid design to enable scale invariance but the method is as before. The original 2D corners are now matched to the frequent configurations using a look-up to the learnt compound features from the first iteration stage, M^1 using a global classifier based on voting.

5.2. Global Classifier

The global classifier exhaustively compares a specific frequent configuration M_α^l , for action α and grouping iteration l , with the original 2D corner combinations in the query transaction set T grouped within their local neighbourhoods. It works as a voting scheme by accumulating the occurrences of the mined compound features within the query transaction vector. This provides a confidence for each set of items within the query transaction vector.

$$Conf_\alpha = Norm * \sum_{i=0}^{sizeof(T)} \sum_{j=0}^{sizeof(M_\alpha^l)} m(T_i, M_\alpha^l) \quad (1)$$

Where $sizeof(T)$ is the number of subsets within T , $Norm$ is the normalisation factor, shown in Equation 2

$$Norm = \frac{1}{sizeof(T) * sizeof(M_\alpha^l)} \quad (2)$$

and $m(T_i, M_\alpha^{l-1})$ describes if a mined compound feature set is present in the transaction vector as in Equation 3

$$m(T_i, M_\alpha^l) = \begin{cases} Conf(T_i \Rightarrow \alpha) & T_i \in M_\alpha^l \\ 0 & otherwise \end{cases} \quad (3)$$

5.3. Scale Invariant grouping

If a transaction vector, T_i , has a confidence greater than zero, the corresponding mined vector, $M_{\alpha j}^l$, is saved as a compound feature. Repeated over all features, this will form compound features for the sequence. Each compound feature has a grid centered over it, however, to allow for scale invariance, only the relative spatial displacement in terms of angle rather than spatial distance is used. This means the grid is adjusted to be 2x2x3. Divided into 12 equal 3D

boxes in the x, y, t domain where x, y radiate from the centre of the neighbourhood out to infinity, and t extends to successive and preceding frames based on ω . The grid design for a single frame is shown in Figure 3. The resulting

Figure 3. Note for illustration a single frame grounding is shown. (a) There are three compound features found on this frame with the IDs 1002, 1005, and 1009, these have been prefixed by there grid location in (b). (c) Shows the concatenation of the compound features into a transaction vector for this interest point.

transactions of the compound features are collated. This stage of training produces around 12 million transactions, with each transaction containing over 1000 items (encoded compound features). Association rule mining is applied to the transactions, to identify the reoccurring compound patterns. This mining is computed in around 30 minutes which is impressive. The resultant frequent configurations M_{α}^2 , contains around 500 association rules.

5.4. Recognition

The resulting Frequent Configurations M_{α}^2 represents the frequent and distinctive itemsets of the training action sequences. To classify an unknown test sequence, the sequence is analysed and the spatio-temporal compound 2D features are detected on a frame by frame basis to form transaction vectors as with the training. These query transaction vectors are then voted on using the global classifier presented previously in section 5.2. This is repeated over the complete test sequence to find the action likelihood of the sequence. A correct match will occur often in equation 3 as the mining will select frequently reoccurring items that are distinct compared to other actions. Each video sequence is then classified as the action, α , for which the votes are maximised.

5.5. Localisation

Each vote from the global classifier on the query transaction vector gives a likelihood of an action. This can be used with a sliding window in order to localise the action. The likelihood is maximised over a window applied at multiple

scales. The windows centre position is moved over the complete image, and an integral image is used for efficiency.

6. Experimental Results

Three sets of data were used to test the approach proposed within this paper. The well known and popular KTH dataset [21] the more challenging, multi-KTH [24], and a real-world example dataset of movie actions [12]. The KTH dataset contains 6 different actions; boxing, hand-waving, hand-clapping, jogging, running and walking. The state of the art accuracy values on the KTH dataset is around 86% to 95%, therefore multi-KTH was proposed to provide more challenging tests. It consists of a single 753 frame long sequence where multiple people perform the KTH actions simultaneously. To increase difficulty, there are large scale changes and camera motion and a non uniform background. The Real-World Movie dataset of Laptev [12] consists of 8 actions; AnswerPhone, GetOutCar, Handshake, HugPerson, Kiss, SitDown, SitUp, StandUp.

6.1. Performance Measures

On the KTH dataset, the data for training and testing can be partitioned in two ways. The partition originally proposed by Schüldt [21] is focused on to allow direct comparison of results. For each action, 8 different people's sequences are used for training and testing. Many authors ignore the partitioning and instead opt for a far easier leave-one-out cross validation. While this is a far similar test, we also report results to allow comparison. For the multi-KTH, accuracy of the localisation is used as the measure of performance. The localisation is deemed correct if the dominant pixel label within the groundtruth bounding box matches the groundtruth. Visual examples of the localisation are shown in Figure 5. The clean test and training partitions used by Laptev [12] were used for the Movie Dataset to allow direct comparison to their published results.

6.2. Action Classification

The classification of the actions within the KTH dataset is performed to allow a comparison of results with other of the state of the art approaches. Figure 4 shows the confusion matrix for the KTH data. There is most confusion occurring between jogging and running and between handclapping and handwaving.

Table 1 shows our proposed technique has a higher classification accuracy than all other state of the art methods. Including **Subseq Boost Nowozin**: The boosted SVM classifier by Nowozin [19], and **Data Mined** The simple single level mining approach by Gilbert [6]

Results within Table 2 use the simpler leave-one-out approach. We also report results using this data with an average performance of 96.7%. Again, this outperforms all

Box	100	0	0	0	0	0
Clap	0	94	6	0	0	0
Wave	0	1	99	0	0	0
Jog	0	0	0	91	7	2
Run	0	0	0	10	89	1
Walk	0	0	0	0	6	94
	box	clap	wave	jog	Run	Walk

Figure 4. Human action recognition results, confusion matrix for KTH dataset

Table 1. Comparison of Average precision compared to other techniques on KTH action recognition Dataset using training/test partition proposed by [21]

Method Schüldt training/test partitions	Average Precision
Gilbert <i>et al</i> [6] Data Mined	89.9%
Nowozin <i>et al</i> [19] Subseq Boost SVM	87.04%
Schüldt <i>et al</i> [21] SVM Split	71.71%
Ke <i>et al</i> [9] Vol Boost	62.97%
Our Approach	94.50%

Table 2. Comparison of Average precision compared to other techniques on KTH action recognition Dataset using leave-one-out cross validation.

Method leave-one-out test/train	Average Precision
Kim <i>et al</i> [10] CCA	95%
Uemura <i>et al</i> [24] Motion Comp Feats	93.7%
Wong and Cipolla [28] Subspace SVM	86.60%
Niebles <i>et al</i> [17] pLSA model	81.50%
Dollar <i>et al</i> [4] Spat-Temp	81.20%
Our Approach	96.7%

other approaches and gives an indication of the complexity of leave-one-out cross validation versus the training, testing split of [21].

To test on the more challenging multi-KTH dataset, the KTH training setup was used and the localised detection results are displayed in Table 3 using the localisation accuracy metric described in section 6.1. The previously published results from Uemura [24] are also shown to provide a benchmark. Our approach has superior performance and has a lower computation costs as is shown in section 6.3. Visual localisation results are shown in Figure 5. In Addition, the approach by Uemura required groundtruthed positions during training to be able to localise actions while our approach required no spatial groundtruth data.

Table 3. Comparison of Average precision of actions compared to other techniques on multi-KTH action recognition Dataset.

	Clap	Wave	Box	Jog	Walk	Ave
[24]	76%	81%	58%	51%	61%	65.4%
Ours	75%	84%	76%	50%	59%	68.8%

Figure 5. Corner Detection on four Frames, (a) KTH Boxing Sequence, (b) KTH Running Sequence (c) Multi-KTH Boxing and Handclapping, (d) Multi-KTH all actions

Comparing the results with the original KTH data, the average accuracy is reduced by just over 25%. This demonstrates the more challenging nature of the multi-KTH data.

6.3. Computation of KTH dataset

One of the advantages of using a data mining technique such as association rules, is the speed of learning patterns within the data. Within this paper the classification and training stages have a low computational cost. This is due to the use of the multi stage hierarchical grouping process. The use of a localised first stage to build compound features, allows high speed matching in the second and main stages where the neighbourhoods are far larger but the number of features far less. To illustrate this, table 4 shows the average frame rate for the stages of the approach. The table shows that the speed of the approach is fast throughout the entire process despite being an unoptimised C++ implementation running on a standard single core desktop PC. In addition the number of features is greatly reduced by the second iteration, this is the main reason for the speed being maintained despite an additional level of complexity. Overall the number of features detected has an effect on the overall speed as can be seen by the differing frame rate between the KTH and the Multi-KTh and Hollywood datasets. However by further increasing the levels of classifier for the more complex sequences could maintain real time operation despite

Table 4. A break down of the average frame per second and features per frame of the successive stages of the classifier

Stage	Frames per second	Ave features per frame
Training Iter 1	35fps	1500
Mining Iter 1	640fps	
Training Iter 2	28fps	300
Mining Iter 2	21fps	
Test KTH	24fps	400
Test multi-KTH	4fps	1500
Test Hollywood	6fps	1300

an increasing number of detected features.

6.4. Real-World movie actions

Training is performed with the clean, manual dataset of 219 videos. The performance is evaluated using the clean test dataset of 217 videos. This is the same as reported by Laptev in [12] to allow for a direct comparison of results. Table 5 presents the average accuracy for the 8 actions. These result show a 15% improvement over the previously

Table 5. Average precision for each action class of the real-world Movie test set. We compare our approach with the previously published results.

Action	[12] Acc	2 Stage Classifier	3 Stage Classifier
AnswerPhone	32.1%	25.7%	41%
GetOutCar	41.5%	38.5%	-
HandShake	32.3%	45.6%	52%
HugPerson	40.6%	42.8%	-
Kiss	53.3%	72.5%	-
SitDown	38.6%	84.6%	9%
SitUp	18.2%	29.4%	31%
StandUp	50.5%	41.6%	24%
Average	38	53.5%	31.4%

published work using the 2 stage classifier, on what is a very difficult but real-world dataset, containing varying camera angles, illumination and people. An illustration of the difficulty is shown in Figure 6 which shows key frames from two sequences within the SitUp class. Using the 3 stage classifier there are promising results in many of the action classes. With three actions showing improved results on the 2 stage classifier. However as the complexity of the compound features increases with additional levels of mining, the number of features that fire reduces. At stage three this becomes a problem and dashes (-) show actions that could not be learnt at stage three due to insufficient data in train-

Figure 6. Key Frames from two SitUp Sequences

ing. This is also evident in reduction of the SitDown action at stage three.

Further analysis of why the approach works was performed, the key point to the method is the combination of spatially grouped compound features. Therefore a test was performed on the movie dataset where the minimum number of items within a mined transaction vector was increased. Table 6 shows the average accuracy and also frame rate as the minimum number of items (compound corners) is increased. The increase in accuracy as the minimum item

Table 6. Average precision of Movie dataset, increasing the minimum number of items within the Transaction vector.

Min No. of Items	2	3	4	5	6
Accuracy	0%	9.6%	21%	52%	54%
Min fps	0.0001	0.002	0.2	3.5	4.5
Max fps	0.001	0.1	2	28	28.5

size increases, indicates that the greater the size of the compound feature the more important it is within the classifier. This is intuitive as the more complex compound features are likely to contain greater discriminative detail for improved inter class disambiguation. The other advantage of the hierarchical approach is that as the minimum number of items is increased, so does the the frame rate. This is due to the reduced total number of transaction vectors within the classifier.

7. Conclusion

This paper has presented a method to recognise and localise actions performed by different humans in real time. This is achieved through the use of compound 2D corner features. The simple corners detected form an overcomplete set of features are encoded with respect to their spatial and temporal neighbourhood. Compound corner groups are formed using a multi-stage grouping. Data mining is used to reduce the overcomplete set to form short feature sets that frequently occur in the training data. These compound features are used to produce localised likelihoods of actions in three sequences; the KTH dataset, the multi-KTH dataset where multiple objects and actions occur simultane-

ously and a real-world Movie dataset. Performance is better than previously achieved results for all datasets, while real time operation is also possible on the datasets due to the implementation of the hierarchical neighbourhood grouping. While the localisation of multiple actions occurs with no object segmentation supplied during training.

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