Object-Centric Spatio-Temporal Pyramids for Egocentric Activity Recognition

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Abstract

Egocentric video and wearable computing have become increasingly prevalent in the past decade, resulting in a huge explosion in the amount of available video content and increased attention from the computer vision community. However, existing methods for activity recognition often use predefined spatio-temporal binning schemes to aggregate features. This encodes information beyond what is possible with a pure "bag of words" model, but is ultimately inflexible and may fail to capture important spatio-temporal relationships between features. We propose to randomly generate a pool of candidate binning schemes and use a boosting algorithm to combine those which are most discriminative. In order to efficiently focus the candidate partition schemes, we create biased partitions using "object-centric" cuts in video volumes. Partition schemes generated using our method have a high probability of cutting through video regions that contain "active objects," the objects being interacted with by the user during a given frame. Given a set of training videos, our method first computes histograms of active object locations across each (x, y, t) dimension, then uses these histograms to generate a pool of object-centric partition schemes that have a high probability of cutting through regions that often contain active objects. We use a boosting algorithm to learn which partitioning schemes are most discriminative and form a final strong classifier. Our main novel contribution is two-fold: we show how to learn the most useful partition schemes in an egocentric setting, and we focus candidate partition schemes by exploiting locations of active objects. Our approach yields state-of-the-art recognition performance, and we find that object-centric partition schemes are often more discriminative than their unbiased counterparts.

1 Introduction

Activity recognition is becoming an increasingly canonical problem in computer vision as researchers are beginning to explore the domain more thoroughly and several relevant datasets have been released [6, 17, 21, 22]. Egocentric activity recognition differs from non-egocentric activity recognition because activities can have long-term temporal dependencies and actions can be interrupted by other actions. A robust and accurate method for egocentric activity recognition would have useful practical applications, such as a memory aid, content-based summarization, or telerehabilitation. For instance, a recent trend in wearable computing is so-called life logging which can assist patients suffering from memory loss [23]. A robust egocentric activity recognition system could automatically tag video clips with their corresponding types of activities. Additionally, there are many clinical benchmarks used to evaluate patients everyday functional abilities [2, 8, 10]. These benchmarks are currently conducted in a hospital setting, but a robust system for egocentric activity recognition could greatly impact the workflow for patient evaluation, allowing for passive long term observation of patients in their own homes. Existing work has made promising progress in both recognition and summarization, [7, 15, 17] yet it remains a challenging problem.

Egocentric activities are well-defined by the types of objects that are interacted with by users during particular actions ("active objects") [17], yet how to optimally aggregate features across space-time remains unclear. The familiar bag-of-words approach can be used to aggregate features with reasonable performance, but ultimately falls short because it fails to capture temporal dependencies between features. The pyramid is a well-known extension of a pure bag-of-words model that encodes spatial relationships between features by recursively subdividing images or video and extracting features from each spatial bin [14], yielding impressive results across a range of applications. Existing methods for activity recognition often rely on hand-coded partition schemes [4, 13, 17]. With a small pool of hand-coded schemes for imposing spatial information, the most discriminative space-time relationships between features may not be captured.

Our idea is to randomly generate a pool of candidate partitioning schemes. We then aggregate spatio-temporal features in a learned way, using a boosting algorithm to select those partitioning schemes which are most discriminative. Boosting is computationally expensive in terms of the number of weak classifiers that are used, and there are many high-dimensional partitioning schemes we could sample. This suggests that a large pool of candidate partition schemes is required to obtain good performance. In order to avoid generation of partitions that are not discriminative, we introduce object-centric partitioning schemes, which have a high probability of cutting through video regions known to contain active objects.

Given a set of labeled training videos with object annotations (bounding boxes and active/passive tags), our method first computes histograms of active object locations across each (x, y, t) dimension of video. We use these histograms to generate a pool of object-centric partition schemes that have a high probability of cutting through regions known to frequently contain active objects. We compute feature vector representations of each training video clip using each candidate in the pool, and use these vectors to train a pool of weak SVM classifiers. Finally, we use a boosting algorithm to select the partitions which are most discriminative and form a final strong classifier.

We find that object-centric partitioning schemes that have a larger number of levels are often the most discriminative in the sense that they tend to get selected by boosting over their unbiased counterparts. We evaluate the performance of our method using a cross-validation experiment and find that our method using object-centric pyramids improves upon the current state of the art.

1.1 Related Work

Activities in a non-egocentric setting can be effectively analyzed based on tracked limb shapes and motion across a video clip as in [18, 19, 21]. An alternative approach involves using lower-level features with weaker semantics such as space-time interest points as in [13, 22]. Previous work on spatial pyramids [1, 14] is extended in [13] by defining the spatio-temporal pyramid representation of video clips, but a relatively small number of predefined schemes for spatio-temporal binning are used, which may fail to capture important spatio-temporal relationships between features. There are 6 possible spatial grids and 4 temporal binning schemes, resulting in a total of 24 possible spatio-temporal partition schemes. Bag of words as a method for pooling of space-time features in video has been analyzed in [4, 5, 13, 16, 17].

Egocentric video is an increasingly popular topic in the computer vision community. Recent work has explored discovery of important people for automatic summarization of egocentric video [15]. The relationship between gaze and activity in an egocentric setting is explored in [7], which presents methods to predict activity given gaze, gaze given activity, and both activity and gaze given neither. Object recognition in an egocentric setting has been explored with promising results by [6, 17, 20]. Activity recognition in an egocentric context has been investigated by [5, 17]. The main work related to our own is that carried out in [17], which introduces the ADL dataset we use to benchmark our method, as well as detailed analysis of the the performance of several different classifiers.

Existing work has established that egocentric activities are object-driven in the sense that visible objects provide useful cues about what types of activities are occurring, rather than tracking of limb position or summarization of overall motion. In other words, egocentric activity recognition is "all about the objects" [17], particularly the objects being interacted with ("active objects"), as recognition accuracy increases dramatically when locations of active objects in addition to passive objects are used as features.

Selection of binning strategies for features in a learned way has been throrougly explored in the spatial domain [9, 24] for image recognition, and some analysis of learning shapes of spatio-temporal regions on a per-class basis using low-level features has been conducted in the video domain [11], but to our knowledge selection of binning strategies in a learned way has not been explored specifically in the egocentric domain.

We use a version of the SAMME multi-class Ada-boost algorithm [25] with randomized spatio-temporal pyramids to explore discriminative selection of partitions for video data, specifically in the egocentric domain.

2 Approach

The goal of our algorithm is to robustly predict what type of activity is occurring in an egocentric video clip. In contrast to other forms of action recognition, egocentric action is "object-driven" in the sense that activities are well-defined by the objects the user is interacting with in a particular video sequence. Figure 1 depicts example frames extracted from video sequences that show the visual differences between passive and active versions of the same objects.

Existing methods for non-egocentric activity recognition often use space-time interest points [12] as features. In other words, in a non-egocentric setting action recognition is often driven by summarization of motion cues throughout video, while object locations can serve as effective features in an egocentric setting.

Active objects, those which are being interacted with by the user in a given video clip, are especially helpful features for egocentric activity recognition [17], yet there is little work in the literature exploring the best ways to pool video features across space-time. A common technique for pooling features is "bag-of-words", an orderless histogram of feature counts. This technique is simple, but does not encode any potentially useful relationships between features in space-time. The "pyramid" is an extension to bag-of-words that encodes space-time relationships between features by recursively subdividing an image or video into multiple subregions and concatenating bag-of-words histograms computed for each region.

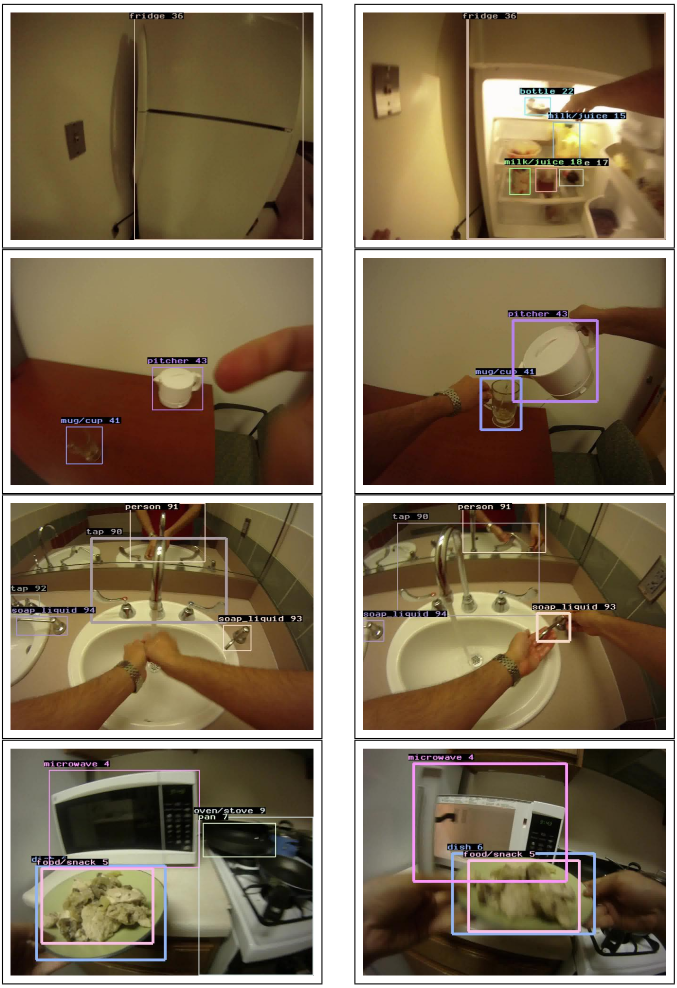


Figure 1: Example frames extracted from the dataset. The left and right columns depict passive and active versions of the same objects, respectively.

Existing work relies on hand-coded partition schemes for computing pyramid representations of datapoints, which is a problematic approach because it is inflexible with respect to new data and can fail to capture the most meaningful relationships between features. To address this problem, we propose to randomly generate a pool of candidate partitioning schemes, then use a multi-class boosting algorithm to learn the most discriminative partition schemes and combine them into a final "strong" classifier.

The intuition behind boosting is to train a set of classifiers and combine their output in such a way as to take advantage of the strengths of each individual classifier. This is accomplished by iteratively training classifiers on the training data. Datapoints are re-weighted after each iteration so that classifiers added during subsequent iterations tend to focus on examples that were previously misclassified.

Our algorithm takes as input a collection of N labeled training videos where (V_i, c_i) denotes a video clip and its associated ground-truth activity label, and a pool of M candidate partition patterns $\{\theta_1, \theta_2, ..., \theta_M\}$. We use the output of the aforementioned object detectors trained on composite object models as our features to be pooled. To convert from object bounding boxes to (x,y,t) coordinates, we simply take the center of each bounding box. Thus, each training example V_i is a set of (o,x,y,t) object locations, where o denotes an object label.

To represent a particular training example V_i using a particular partition scheme θ, we compute separate bag-of-words histograms for each level in θ, and concatenate all such histograms to form a final feature vector used in training. We initialize a weight w_i for each training example V_i that is inversely proportional to the number of points with the same class as V_i. Giving larger weights to training examples of infrequently occurring actions helps to mitigate any bias resulting from imbalanced training data.

We train a separate "weak" multi-class SVM (using LIBSVM [3]) classifier on the feature vectors resulting from representing the training data using each candidate partition pattern θ. During each round of boosting we select the candidate partition θ_j that is most discriminative (has minimum weighted training error, which is computed as the dot product between the weight vector w and an indicator of incorrect classifications using f_θ). Next, we compute a weight for θ_j based on how many training examples were misclassified using f_{θ_j}, the classifier that was trained using the representation of the training data under θ_j. At the end of each boosting iteration, we update the weights for each training example. Training examples that were previously misclassified are assigned higher weights to encourage correct classification in future boosting rounds. Finally, we generate the final strong classifier F, which maximizes a weighted sum of correct classifications produced by each weak classifier.

Algorithm 1: Training RSTP Classifier via Multi-Class Boosting
INPUT:

- N labeled training videos $\Phi = \{(V_i, c_i)\}_{i=1}^N$
- A pool of M partition patterns $\Theta = \{\theta\}$

OUTPUT:

- A strong video classifier F. For an unlabeled video V, $c = F(V)$ is the predicted label for V.

1. For each $\theta \in \Theta$:

- Compute the representations of each $V_i \in \Phi$ using θ and train a multi-class classifier (SVM) f_θ on the resulting feature vectors.

2. Initialize:

- A weight $w_i = \frac{1}{CN_{c_i}}$ for each video clip, where N_{c_i} is the number of videos with label c_i, and C is the number of distinct labels in the training data.
- Current iteration number $j = 0$.
- Current accuracy $\sigma_j = 0$.

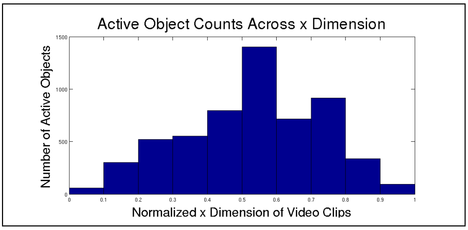
3. For each round of boosting:

- Increment j.
- Re-normalize the weight vector:
$$\forall i, w_i = \frac{w_i}{\Sigma_i^N w_i}.$$
- For each pattern θ, compute its weighted classification error:
$$e_\theta = w \cdot \mathbf{I}(f_\theta(V) \neq c)$$
- Choose the pattern θ_j with minimum weighted classification error e_j.
- Compute the weight for θ_j:
$$\alpha_j = \log \frac{1-e_j}{e_j} + \log(C-1)$$
- Update the weight vector:
$$w_i = w_i \cdot \exp(\alpha_j \cdot \mathbf{I}(f_{\theta_j}(V_i) \neq c_i)).$$
- Generate the current strong classifier:
$$F(V) = \text{argmax}_c \Sigma_{m=1}^{j} \alpha_m \cdot \mathbf{I}(f_{\theta_m}(V) = c)$$

2.1 Generating Randomized Spatio-Temporal Partitions (RSTP)

An RSTP is generated using a hierarchical partitioning of feature space. We generate cuts independently in a round-robin manner over dimensions (x,y,t). Each cut is axis-aligned (we incorporate random shifts, but not random rotations). To construct a partition scheme that is easily applicable to videos of arbitrary size, we consider partitioning an "idealized" video clip that has all dimensions normalized to length 1. To generate a single cut we sample a random number from a uniform distribution subject to any constraints imposed by "parent cuts" and use this as a randomized offset for an appropriate axis-aligned plane. To construct an unbiased partition scheme we sample from a uniform distribution.

To represent a video clip as a randomized spatio-temporal pyramid (RSTP) using a particular partition scheme we use the output of object detectors trained in [17], which gives bounding boxes and object labels for each extracted frame. We use centroids of bounding boxes to obtain (x,y,t) coordinates for each individual object. We compute histograms of detected objects for each individual level in the pyramid, where level 0 is the entire video clip volume and level i is all the cells of depth i in the pyramid. Note that level i has 8^i leaf cells. To form the final RSTP representation, we concatenate the histograms computed for each level to form a single feature vector. We can choose whether or not to include detected



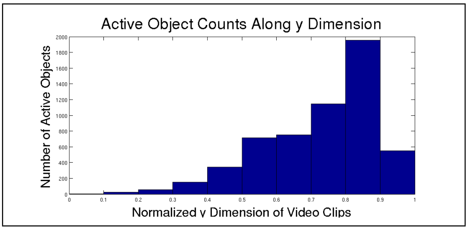


Figure 2: Histograms of detected active objects across the x and y spatial dimensions of training data. Active objects tend to appear in the lower center field of view. There is a slight bias favoring the right side of the field of view because many users are right-handed.

active objects when forming an RSTP representation of a video clip, however taking active objects into account gives a substantial improvement to overall classification accuracy. Figure 4(a) depicts a potential partitioning scheme that could arise when using uniform partition generation. In this case, the partition is not likely to be discriminative because all objects are located in a single region.

2.2 Generating Object-Centric Cuts (OCC)

There are many high-dimensional partition schemes that we could sample randomly, which suggests that a very large pool of candidate partition schemes is required to obtain good results. However, boosting is computationally expensive, so we would like to minimize the size of the pool while maintaining good results. One of the main contributions of our work is the ability to generate meaningfully biased randomized partition schemes that tend to be more discriminative than their unbiased counterparts. To accomplish this, we propose to replace the uniform distribution with a discrete approximation of the distribution of active objects across each dimension (x,y,t) and otherwise proceed normally. Figure 4(b) depicts a potential partitioning scheme that could arise when using object-centric partitioning. In this case, the example bin boundaries lie in a region containing an active object (tv remote), and the resulting partition scheme is likely to be more discriminative.

From figure 2 we see that active objects often tend to occur in the lower center of the field of view. This conforms to our expectations, because the active objects are close to the hands which are in the lower field of view from an egocentric perspective. Active objects tend to occur on the right side of the field of view slightly more often because a large percentage of users are right-handed. The distribution of active objects across the temporal dimension is nearly uniform. This distribution is computed across all action types; we do not compute separate active object distributions for each action class. Since different clips can have varying lengths with respect to time, we normalize the length of each video clip to 1 and consider relative temporal locations of active objects. For biased partitions, we generate the first split along each dimension according to a distribution corresponding to the histograms of observed active object regions in the training data, and we generate all subsequent child cuts using a uniform distribution. For example, when generating a biased cut for the y dimension, we generate a random number between 0 and 1 that has a high probability of being in the range $(0.5, 0.9)$. We do not consider locations of passive objects at all during the generation of biased partition schemes. Since active objects are located in close spatial proximity to hands, creating object-centric partition schemes can be interpreted as implicitly taking into

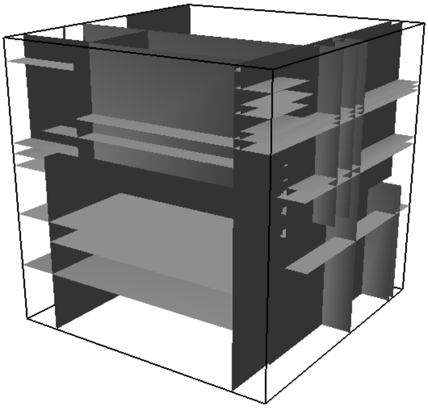


Figure 3: An example 3-level object-centric partitioning scheme. Visible cuts along the y dimension correspond to locations known to frequently contain active objects.

account information about hand locations.

Figure 3 depicts an example 3-level object-centric partition scheme. The salient feature to note is that visible splits along the y dimension correspond to the observed distribution of active objects along the y dimension of the training data.

2.3 Complexity and Runtime

The asymptotic complexity of training with N training examples and a pool of M candidate partition schemes with l levels using our method is

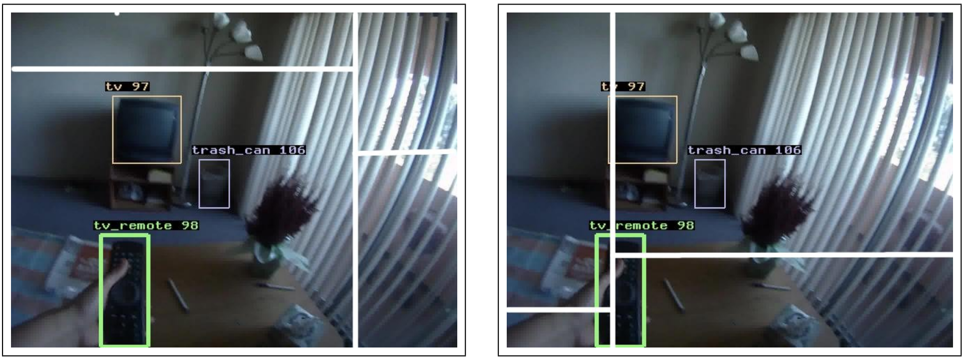
$$O(N \cdot M \cdot 8^l \cdot t_{train} + b \cdot (N + M \cdot t_{test}))$$

where b denotes the number of boosting rounds, and t_{train} and t_{test} denote the time to train and test a single SVM classifier on N feature vectors, respectively. Fortunately, l remains small (never exceeds 4 in our experiments). In order to predict the label for a single test video clip v, we first need to compute representations of v using each partition scheme that was selected during boosting, then find the class c which maximizes a weighted sum of matching classifications using each weak classifier selected during boosting. Thus, the overall asymptotic complexity of predicting the label for a single video clip is

$$O(b \cdot 8^l + C \cdot b \cdot t)$$

where b is the number of boosting rounds, C is the number of possible activity labels, and t is the time to predict the label of a test example using a weak SVM classifier.

Figure 5 depicts empirically determined running times for our method on a single "fold" of the cross-validation experiment described in section 3.1. For each pool size we present mean execution time across 5 separate executions. Running time is linear with respect to pool size.



(a) (b)

Figure 4: Potential partition schemes that could result using uniform (a) and object-centric (b) partition generation. The partition scheme resulting from using object-centric partition is likely to be more discriminative.

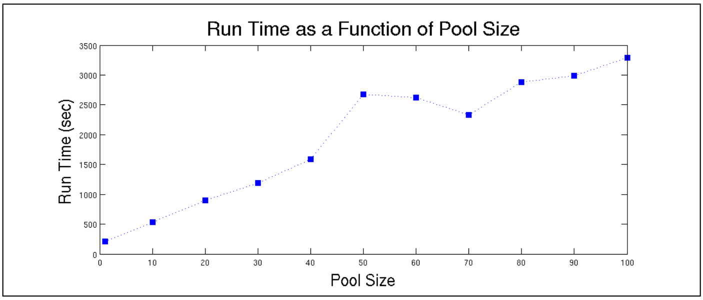


Figure 5: Running times for our method as a function of pool size.

label	activity type
1	combing hair
2	make up
3	brushing teeth
4	dental floss
5	washing hands/face
6	drying hands/face
7	laundry
8	washing dishes
9	moving dishes
10	making tea
11	making coffee
12	drinking water/bottle
13	drinking water/tap
14	preparing cold food/snack
15	vacuuming
16	watching tv
17	using computer
18	using cell phone

label	object type
1	fridge (active)
2	microwave (active)
3	mug/cup (active)
4	oven/stove (active)
5	soap liquid (active)
6	bed (passive)
7	book (passive)
8	bottle (passive)
9	cell phone (passive)
10	dental floss (passive)
11	detergent (passive)
12	dish (passive)
13	door (passive)
14	fridge (passive)
15	kettle (passive)
16	laptop (passive)
17	microwave (passive)
18	monitor (passive)
19	pan (passive)
20	pitcher (passive)
21	soap liquid (passive)
22	tap (passive)
23	tea bag (passive)
24	toothpaste (passive)
25	television (passive)
26	tv remote (passive)

Table 1: Lists of action types and object types present in the ADL dataset. Separate active and passive models are trained for fridge, microwave, mug/cup, oven/stove, and soap liquid.

3 Results

In this section we briefly describe properties of the dataset we use to benchmark our method and present results from experiments we conducted. We evaluate our overall recognition accuracy and show that it improves the current state of the art, and we demonstrate the superior discriminative power of object-centric partition schemes.

The ADL dataset consists of hundreds of egocentric video clips (roughly 10 hours of video in total) collected from 20 people performing 18 types of unscripted actions in their own homes. These naturally occurring actions are often related to hygiene or food preparation and are more varied than actions presented in previous datasets such as that of [6]. There are 26 different types of detected objects, including 5 active and 21 passive objects. Lists of activity types and object types are given in Table 1. Object detectors are trained on videos from the first 6 people and tested on the videos from the remaining 14 people.

Each frame in the dataset is annotated with activity labels and bounding boxes for detected objects and hand positions, Additionally, each object is tagged as active or passive depending on whether it is being interacted with.

One difficulty that can arise within egocentric activity recognition is that activities can be temporarily interrupted by other activities. For instance, while waiting for tea to brew a subject may watch TV. For cases of such interruptions, to avoid unnecessary complications

BoW	Temporal Pyramid [17]	RSTP	RSTP+OCC
34.9%	36.9%	33.7%	38.7%

Table 2: Overall classification accuracy on pre-segmented video clips, evaluated using a form of cross validation. Our boosted RSTP+OCC classifier improves on the current state of the art.

resulting from frames being annotated with multiple activities, the ADL dataset simply uses the label of the interrupting action when a longer action is disrupted.

The ADL dataset has been modified since the publication of [17]; because of this, running the published code gives slightly lower accuracy than the originally published numbers. We use the modified version of the dataset available from the authors webpage at the time of writing to benchmark our method.

3.1 Action Recognition Performance

Following [17], we evaluate recognition performance on the ADL dataset using a form of cross validation (the video clips from person i are used as a held out validation set, and training occurs using the video clips from the remaining people). We exclude videos from the first 6 people (because they were used to train the object detectors) from our experiments.

Table 2 shows a comparison of overall classification accuracy between our approach and the method based on temporal pyramids which is presented in [17]. The temporal pyramid has two levels, formed by making a single cut along the temporal dimension and no cuts along the spatial dimensions. These results were obtained using both active (being interacted with) and passive detected objects. The consideration of active objects when constructing feature vectors gives a significant improvement over just including passive objects.

For this experiment we tried pools of 4-level partitioning schemes of varying sizes with a varying number of boosting rounds. The numbers presented in Table 2 were obtained with 5 boosting rounds and a pool of size 70. The work of [9], which uses a similar pyramid-based boosting approach for 2D image recognition, found that using pyramids with more than 3 levels actually led to a decrease in overall accuracy due to over-segmentation of image space. However, we found that in the 3D case 4-level pyramids give better overall accuracy than coarser-grained representations.

As seen in Figure 6, our method has particularly good performance for activity types 5 and 6 (“combing hair” and “drying hands/face”, respectively). Some activity types on which our method does poorly are 10 and 11, which are “making tea” and “making coffee”, respectively (see Table 1 for a full listing of activity types present in the ADL dataset). Since the two activity types are similar in the sense that they involve the same active objects, it is not unexpected that a recognition system would confuse them often. Furthermore, since the distributions of objects across space-time are similar, and kettles and tea bags are not modelled in an active way, it is difficult for our boosting algorithm to select partitioning schemes that are discriminative for these classes. An extension of our method which allowed selection of discriminative partition schemes on a per-class basis could allow for more fine-grained control and could help mitigate such issues.

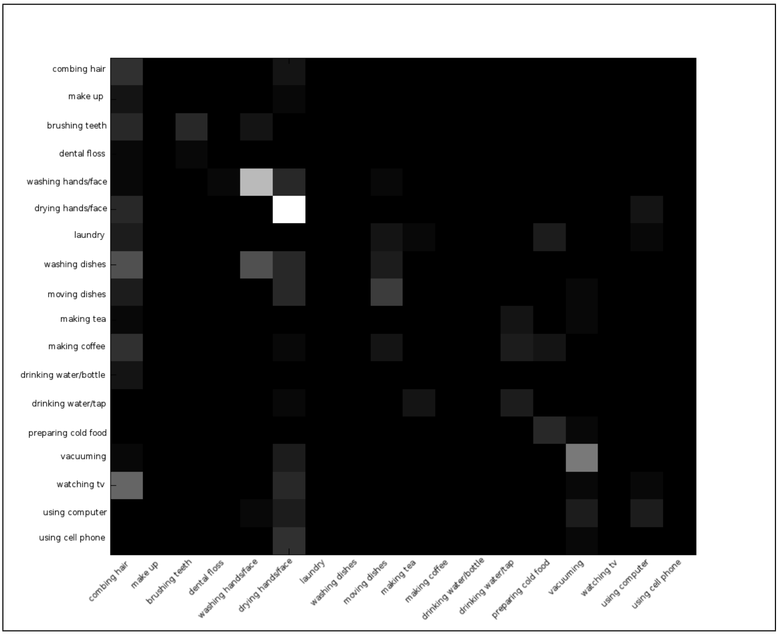


Figure 6: Confusion matrix for RSTP+OCC using detected active and passive objects

3.2 Effect of Object-Centric Partition Schemes

To concretely illustrate the improvement obtained from using a object-centric partitions, we created separate pools containing 4-level partition schemes of each bias type and repeatedly ran our boosting algorithm, computing training error and adding additional partitions to each pool between runs. Results from this experiment are depicted in Figure 7. The pool containing object-centric partitions usually had a lower training error than the unbiased pool. Larger improvements are visible with smaller pool sizes, and the difference between the two pools diminishes as pool size increases. This conforms to expectations because as the unbiased pool grows in size, it becomes more likely to contain discriminative partition schemes, while the biased pool is forced to contain discriminative partition schemes even at relatively small pool sizes. This result suggests that by using object-centric partitions rather than unbiased partitions, we can obtain good recognition results even with a smaller pool, making our boosting algorithm less expensive to compute.

4 Conclusion and Future Work

Our main novel contribution is two-fold. We show how to learn the most discriminative partition schemes for spatio-temporal binning in video feature space, and we introduce object-centric partition schemes, which have a high probability of cutting through video regions known to frequently contain active objects. Unlike previous work, we randomly generate a pool of candidate partitioning schemes and select those which are most discriminative using a boosting algorithm. Our recognition approach improves on the current state of the art, and our experiments demonstrate the positive impact of taking active object locations into

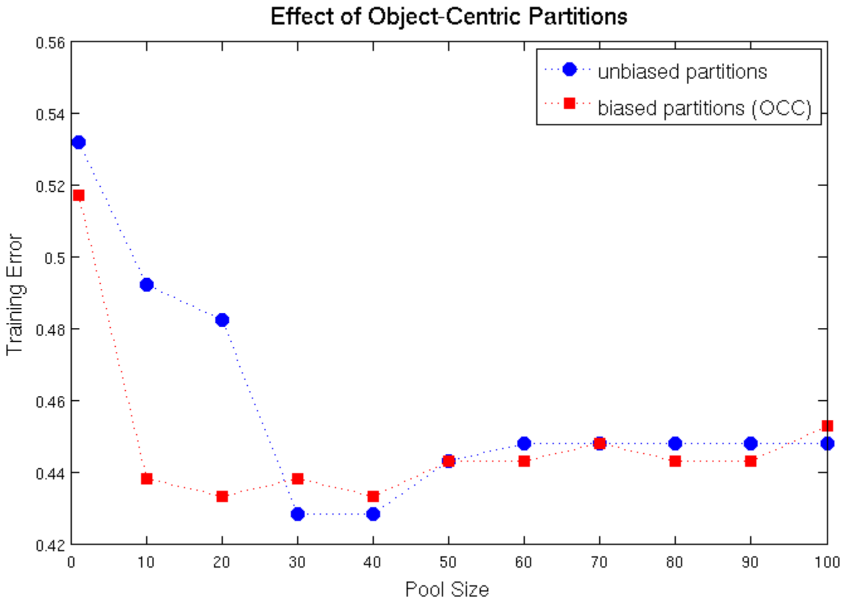


Figure 7: Effect of using biased partition schemes. The object-centric pool usually has lower training error than the pool of unbiased partition schemes. The most significant improvement is visible at smaller pool sizes.

account by generating object-centric partition schemes.

In future work, we intend to investigate ways of learning the most discriminative partition schemes on a per-class basis. Additionally, it may be possible to incorporate different types of biases when generating partitions. The ADL dataset also includes annotations for hand positions, which we have incorporated implicitly through our generation of object-centric cuts. However, it could be possible to incorporate explicit information given by hand positions to obtain better results. The partitions we focus on contain cuts that are planar and axis-aligned (we consider random shifts but not random rotations, and we do not consider non-planar splits), but it is possible to carve up the video volume in more advanced non-linear ways. Such a method would make histogram computation more expensive , but may yield a more discriminative partitioning scheme that could lead to better classification accuracy.

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