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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. Activity recognition is a challenging task with many interesting applications. In egocentric video, activities are largely defined by the objects being interacted with by the camera wearer. As an extension to simply computing a histogram of objects, spatio-temporal binning approaches are able to capture relative space-time relationships between features. However, existing methods for activity recognition often use predefined spatio-temporal binning schemes (such as a hierarchy of uniformly spaced partitions) 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. To overcome this limitation, we propose to learn the spatio-temporal partitions that are most discriminative for egocentric activities. We develop a boosting approach that automatically selects the best spatio-temporal partitions from a pool of randomly generated candidates. In order to efficiently focus the candidate partition schemes, we further propose to create biased partitions using "object-centric" cuts in video volumes. The object-centric cutting scheme prefers to sample bin boundaries near objects involved in egocentric activities. This approach specializes the randomized pool for the egocentric setting and improves training efficiency. Our proposed method yields state-of-the-art accuracy for the challenging task of recognizing activities of daily living.

1 Introduction

Computer vision in an egocentric context involves the analysis of images and video captured by a wearable camera, typically mounted on the head or chest of the user. Viewing the world from this first-person perspective gives rise to a host of interesting new applications and challenges. 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 everyday functional abilities of patients undergoing physical rehabilitation [11, 2, 9]. 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. Such applications demand robust methods for activity recognition in an egocentric context. Existing work has shown promising progress in egocentric activity recognition [17, 6], yet it remains a challenging problem.

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. Furthermore, whereas activity analysis in the traditional "third-person" view is driven by models of optical flow or human body pose, egocentric activities are well-defined by the types of objects that are interacted with by users during particular actions ("active objects") [17]. Thus, using detected objects is a promising way to encode egocentric video clips, yet how to optimally aggregate features across space-time remains unclear. The familiar bag-of-objects 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 [17, 4, 13]. By using manually defined schemes for imposing spatial information, the most discriminative space-time relationships between features may not be captured.

To overcome this limitation, we propose to learn the most discriminative histogram partition schemes for egocentric activity analysis. Instead of using manually defined binning structures, we develop a boosting approach that identifies and selects the best partition schemes from a pool of randomly generated candidates. Boosting is a general learning framework that allows one to combined multiple "weak" classifiers (better than chance) into a "strong" classifier with good performance. This process 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 further propose a method for meaningfully biasing the pool of candidates. In particular, we introduce "object-centric" partitioning schemes, which prefer to sample bin boundaries near objects involved in egocentric activities, such as an open microwave or a cup in the users hand.

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 tend to have bin boundaries in regions containing human-object interactions. 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 experimentally evaluate the performance of our method using the challenging Activities of Daily Living dataset, demonstrating both an improvement to the state of the art and the key role played by object-centric cuts as a way to focus the pool of candidates.

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 [22, 13, 16], which attempts to directly learn motion patterns associated with specific activity classes. A fairly standard pipeline has emerged, similar to that used for image classification: detection of space-time interest points, extraction of local descriptors, quantization to space-time visual words, and representation using a histogram of visual word counts. Bag-of-words as a method for pooling of space-time features in video has been analyzed in [4, 13, 17, 16, 5].

Since a pure bag-of-words does not have any notion of order or space-time relationships between features, researchers have drawn inspiration from previous work on spatial pyramid image representation [1, 14] to construct space-time histograms from space-time sub-regions of the video volume [13, 17]. Such representations count the number of features appearing in each sub-region, and thus are able to encode the relative layout of features in space-time. In [13], a set of spatio-temporal bin structures is developed using 6 possible spatial grids and 4 temporal binning schemes, resulting in a total of 24 possible spatio-temporal partition schemes. A summed kernel is used to combine the histograms from all partitions. In [4], features are pooled at multiple resolutions using a hierarchy of regularly sized cubic bins. Similarly, it is possible to hierarchically bin neighboring local features and learn which space-time weightings are most discriminative as in [12]. In the egocentric setting, a temporal pyramid that divides the video into two equally sized regions along the temporal dimension (and makes no spatial cuts) is proposed and used to bin the outputs of object detectors [17]. Unlike such approaches, we propose to learn which pyramid partition structures are most informative.

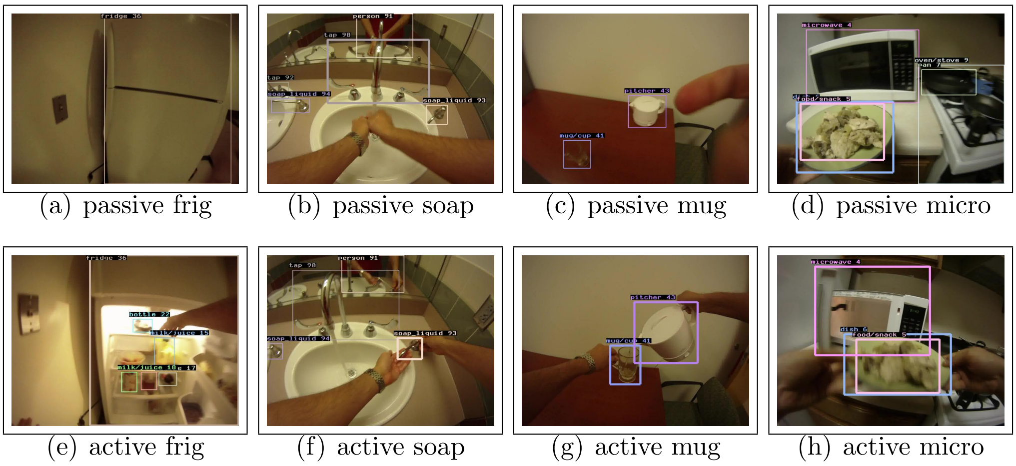
Egocentric video is an increasingly popular topic in the computer vision community. Some prior work using data from wearable cameras considers a specific environment in which familiar individual objects are informative [5, 8, 26] or leverages data obtained from additional sensors [25]. In contrast, we are interested in classifying unscripted activities performed by a camera wearer moving in multiple environments without pre-placed objects of interest or any additional sensors. Such a scenario is also investigated by [17], which also found 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 pose 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.

Aside from activity recognition, analysis of egocentric video also gives rise to other interesting problems and challenges. For example, 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 [6]. Object recognition in an egocentric setting has been explored with promising results by [17, 7, 20].

Selection of binning strategies for features in a learned way has been explored in the spatial domain [24, 10] for image recognition, but to our knowledge no prior work considers learning spatio-temporal partitions in the video domain, egocentric or otherwise. Additionally, our biased partitions based on object interactions are both novel and critical for good recognition results.

2 Approach

The goal of our algorithm is to robustly predict what type of activity is occurring in an egocentric video clip. Given a set of training videos labeled with their particular activity classes, we first extract locations of objects. Objects are classified as “active” or “passive” based on whether they are being interacted with by the user during particular frames. Next, we construct a pool of candidate space-time pyramids. In each pyramid, each axis-aligned bin boundary is translated by some randomized shift. For those pyramids which are object-centric, such shifts are sampled non-uniformly; they correspond to the empirically observed distributions of active object coordinates in the training data. Finally, we use a multi-class boosting algorithm to generate a robust classifier, selecting candidates based on how well they are able to classify training examples. The following subsections describe each step in more detail.



(a) passive frig (b) passive soap (c) passive mug (d) passive micro

(e) active frig (f) active soap (g) active mug (h) active micro

Figure 1: Example passive and active instances of four objects in ADL [17].

2.1 Detecting Active and Passive Objects

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. Thus, we construct our representation based on the locations of objects in space-time.

Following [17], we make a distinction between active and passive versions of the same objects, noting that an object can have a vastly different appearance based on whether or not is is being interacted with. For example, an open refrigerator that is being interacted with looks quite different than one that is being passed by. Figure 1 depicts example frames extracted from video sequences that show the visual differences between passive and active versions of the same objects.

In contract to existing work, we exploit this distinction to provide a semantically meaningful bias regarding where space-time partition boundaries ought to be placed. We use the output (bounding boxes) of composite deformable part model object detectors for active and passive versions of various objects as our features to be pooled. These detectors were originally trained in [17]. We extract an (x, y, t) coordinate for each detected object by computing the center of its predicted bounding box, and we count an object as occupying the space-time bin that the center of its bounding box occupies.

2.2 Generating Randomized Object-Centric Space-Time Pyramids

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.

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.

A Randomized Spatio-Temporal Pyramid (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 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 centers 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

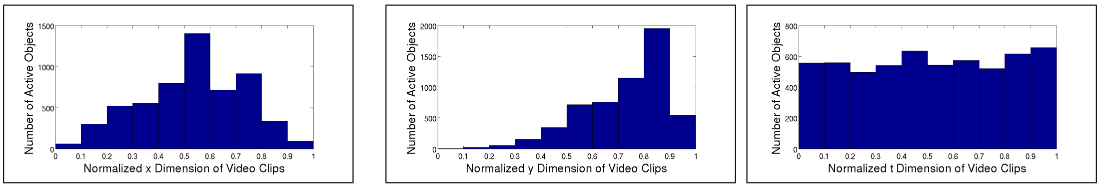
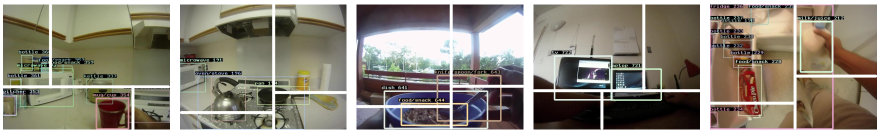


Figure 2: Histograms of detected active objects across the x, y, and t dimensions of training data.

for each level to form a single feature vector.

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.

To generate Object-Centric Cuts (OCCs), we first compute histograms of active object locations across each (x, y, t) dimension of the training data. Figure 2 shows 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 coordinates 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



(a) Object-centric cuts

(b) Uniformly random shifts

Figure 3: Example partitions using either object-centric (a) or uniformly sampled randomized cuts (b). Note that for display purposes we show cuts on example 2D frames, but all cuts are 3D in space-time. Using the proposed object-centric cuts, we better focus histograms surrounding the human-object interactions.

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 account information about hand locations.

Figure 3 depicts some example frames overlayed with randomized shifts sampled using our object-centric strategy (a) and the simple uniform strategy (b). The depicted object detections are from the ADL repository [17]. Object-centric cuts successfully focus the histogram bin boundaries on space-time regions where users interact with objects. Thus, they may offer useful discriminative cues to the boosted classifier.

Figure 4 depicts an example 2-level object-centric partition scheme. The salient feature to note is that visible splits along the x and y dimensions correspond to the observed distribution of active objects along the x and y dimensions of the training data.

2.3 Boosting Discriminative Spatio-Temporal Pyramids

Once we have constructed a pool of randomized object-centric pyramids, we use a boosting algorithm to select those which are most discriminative for egocentric

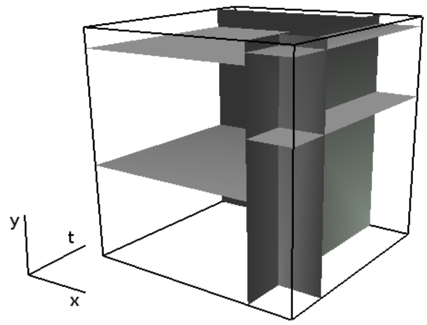


Figure 4: An example 2-level object-centric partitioning scheme

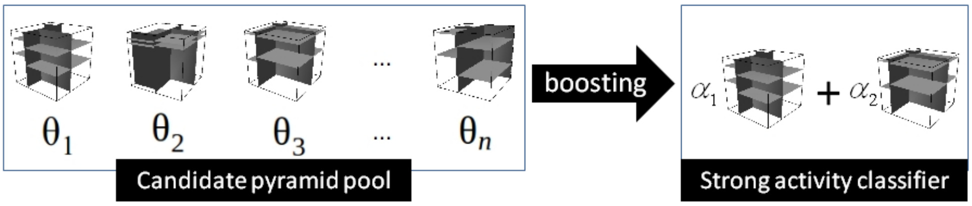


Figure 5: We take a pool of randomized space-time pyramids with object-centric cuts, and use boosting to select those that are most discriminative for egocentric activity recognition.

activity recognition (see Figure 5).

The intuition behind boosting is to train a set of "weak" classifiers (better than chance) and combine their output to form a "strong" classifier in such a way as to take advantage of the strengths of each individual weak 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. Each weak classifier is a non-linear (polynomial kernel) SVM trained using one RSTP with OCC's.

We use the Stage-wise Additive Modeling using a Multi-class Exponential loss function (SAMME) boosting approach of [27], which is a natural extension of the original AdaBoost algorithm to a multi-class classification task without a reduction to multiple binary classification problems. We selected this algorithm because it avoids training individual classifiers for multiple one-vs.-all or one-vs.-one classification problems.

For our method, SAMME boosting works as follows. We take 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.

Given a novel test video V, we compute object locations, then extract only those RSTP histograms that were selected during the boosting algorithm, and then apply F to V to robustly predict its activity label. Algorithm 1 summarizes these steps in more detail.

Algorithm 1: Training a space-time pyramid classifier with boosting

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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 pattern $\theta \in \Theta$:
   - Represent each $V_i \in \Phi$ using θ and train an SVM classifier f_θ on the resulting feature vectors.
2. Initialize:
   - A weight vector w with $w_i = \frac{1}{CN_{c_i}}$ for each video where N_{c_i} is the number of videos with label c_i, and C is the number of distinct action labels.
   - Current boosting round $j = 0$.
3. For each round of boosting:
   - Increment j and re-normalize the weight vector w.
   - 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 as: $\alpha_j = \log\frac{1-e_j}{e_j} + \log(C-1)$
   - Update the weight vector w: $\forall i : w_i = w_i \cdot \exp(\alpha_j \cdot \mathbf{I}(f_{\theta_j}(V_i) \neq c_i))$.
   - Generate the current strong classifier: $F(V) = \text{argmax}_c \Sigma_{m=1}^{j} \alpha_m \cdot \mathbf{I}(f_{\theta_m}(V) = c)$

2.4 Complexity and Training Time

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

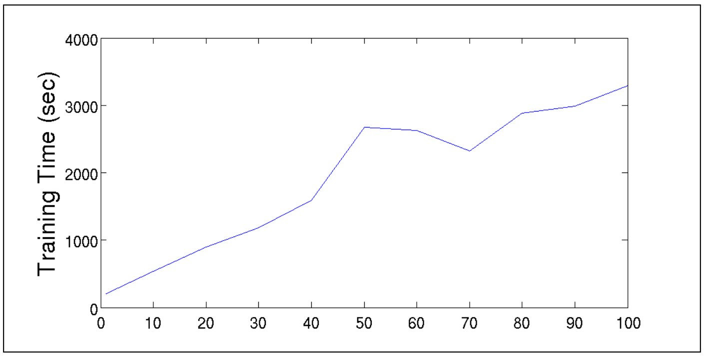

Figure 6: Training times for our method as a function of pool size.

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

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 6 depicts empirically determined training 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. Training time is linear with respect to pool size.

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

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.

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 [7]. 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 automatically 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 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.

For this experiment we tried pools of 4-level partitioning schemes of varying sizes with a varying number of boosting rounds. We used 5 boosting rounds and a pool of size 70. These results were obtained using both active (being interacted with) and passive detected objects.

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 first baseline, bag-of-words uses space-time interest points, a standard representation for action recognition in the third-person case. The second baseline uses a bag of detected objects. The third baseline, the temporal pyramid as first proposed in [17], has two levels, formed by making a single cut along the temporal dimension and no cuts along the spatial dimensions. The temporal pyramid represents the state of the art on this dataset. The fourth baseline, RSTP, is similar to our proposed approach, except it uses cuts sampled from a uniform distribution instead of object-centric cuts.

BoW	Bag-of-objects	TempPyr [17]	Boost-RSTP	Boost-RSTP+OCC (ours)
16.5%	34.9%	36.9%	33.7%	**38.7%**

Table 2: Overall classification accuracy on ADL. Our method improves the state of the art.

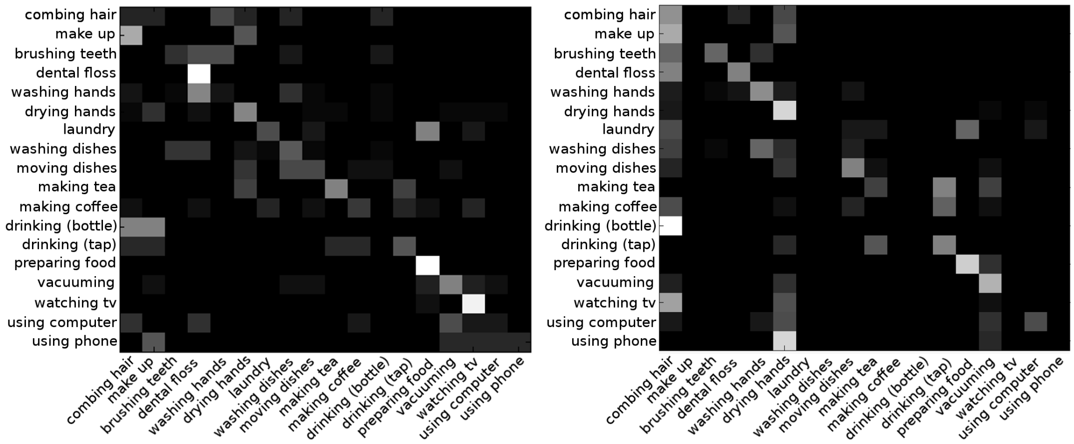

Figure 7: Confusion matrices for temporal pyramid [17] (left, 36.9%) and RSTP+OCC using detected active and passive objects (right, 38.7%).

Our approach outperforms all four baselines, improving on the state of the art. Compared to the bag of words approach, our method has the advantage of using high-level features (object coordinates). The temporal pyramid also has this advantage, but relies on a manually defined binning structure, making it weaker than our proposed method. Object-centric cuts are essential for our recognition result, as simply using cuts drawn from a uniform distribution leads to noticeably weaker performance. This supports our claim that biasing bins according to human-object interactions provides useful cues for recognition in an egocentric context.

As seen in Figure 7, our method has particularly good performance for "combing hair" and "drying hands/face", suggesting that our boosting approach was able to usefully isolate the space-time relationships present in these actions. The temporal pyramid likely yields worse performance on "combing hair" and "drying hands/face" because a single cut along the temporal dimension is not sufficient to isolate the relevant space-time relationships. This indicates that the spatial cuts we learn are essential for scenes with similar objects throughout different action. For example, floss or toothpaste might be visible on the counter while the user is combing hair, but when actually in use, floss or toothpaste would appear higher in the field of view.

On the other hand, some action types on which we do poorly 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 modeled 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, however this is left for future work.

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 8. 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.

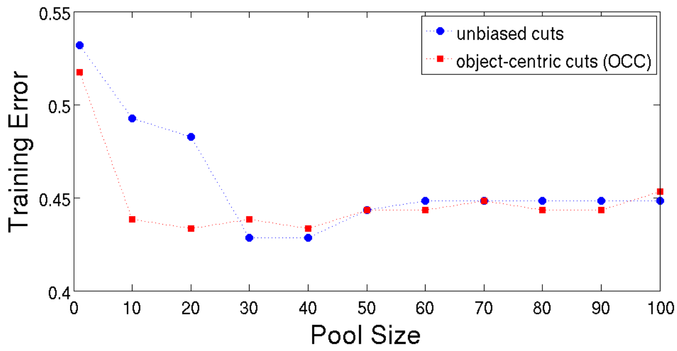

Figure 8: Effect of using biased partition schemes. The object-centric pool usually has lower training error than the pool of unbiased partition schemes. The most significant improvement is visible at smaller pool sizes.

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 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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