Ego-object discovery

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ABSTRACT

Lifelogging devices are spreading faster everyday. This growth can represent great benefits to develop methods for extraction of meaningful information about the user wearing the device and his/her environment. In this paper, we propose a semi-supervised strategy for easily discovering objects relevant to the person wearing a first-person camera. Given an egocentric video sequence acquired by the camera, our algorithm uses both the appearance extracted by means of a convolutional neural network and an object refill methodology that allows to discover objects even in case of small amount of object appearance in the collection of images. A SVM filtering strategy is applied to deal with the great part of the False Positive object candidates found by most of the state of the art object detectors. We validate our method on a new egocentric dataset of 4912 daily images acquired by 4 persons as well as on both PASCAL 2012 and MSRC datasets. We obtain for all of them results that largely outperform the state of the art approach. We make public both the EDUB dataset\textsuperscript{1} and the algorithm code\textsuperscript{2}.

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1. Introduction

Ubiquitous computing is more present everyday in our lives, and with it lifelogging devices \cite{Hodges2006,Michael2013} are increasing their popularity and spread. By using wearable cameras, we can acquire continuous data about the life of persons, and build applications that convert this huge amount of data into meaningful information about their lifestyle. Hence, wearable cameras offer an easy manner to acquire information about our daily life tasks, and extract information about our typical activities and habits. For example, Fig. 1 shows datasets acquired in three days by 3 different users. We can observe that different persons have different environments. Probably, the most remarkable reason for being able to detect visually the differences in the users’ datasets, is usually due to the distribution and aspect of scenes, objects and people that appear. Following these premises, in this paper, we address the problem of automatically discovering which are the usual objects that form the environment of a person wearing the camera by means of a novel Object Discovery (OD) method.

Several works have been previously done in the OD field, some using segmentation techniques \cite{Schulter2013,Russell2006}, others extracting objects relying on visual words \cite{Russell2006,Sivic2005,Liu2013}. Note how objects help to discriminate different environments.
The article is organized as follows: in section 2, we define the EOD algorithm. In section 3, we present the datasets used to validate our method, the tests of EOD on all datasets, comparison to state of the art object detection and discussions on the obtained results. The article finishes with conclusions and future work.

2. The Ego-Object Discovery Approach

Given the problem of OD in low-temporal resolution egocentric data, our algorithm is provided with a seed of initial knowledge to expand. It is defined as a small bag of labeled objects, represented by their regions, which we call a bag of refill. The EOD algorithm passes iteratively through several steps: a) it extracts image regions representing object candidates and their corresponding objectness scores from each new image (or set of images), b) filters ‘No Object’ instances and c) proceeds with a clustering-based procedure: 1) on the easiest objects, it applies a refill strategy, 2) clusters them and labels the best cluster representing the newly discovered object and 3) applies a supervised expansion to find harder instances of it (see Fig. 2).

To describe and cluster the candidates, EOD uses both appearance and local context features. Appearance are extracted by a CNN (Jia, 2013), and context is provided by both the inherent description of the object background by the CNN and the refill procedure, very suitable for egocentric images.

2.1. Object Candidates Generation

The object candidates extraction, we used in the first step, relies on the use of an object detection algorithm. In order to achieve an iterative easy-first discovery, we used an objectness score provided by the Ferrari’s objectness detector defined in (Alexe et al., 2010). The objectness score selection determines, if a candidate $\omega$ is considered in the current iteration: $\text{objectnessScore}(\omega) > \mu + \omega_1 \sigma - \omega_2 t$, where $\mu$ and $\sigma$ are respectively, the mean and the standard deviation of all scores, $t$ is the current iteration, and $\omega_1$ and $\omega_2$ are weights.

SVM-based object candidates filtering: The main drawback of object detection methods is the huge number of FP.
Given that it is not enough to rely on the objectness score for discarding the 'No Object' instances, we filter the object candidates (a strategy applied successfully in other works (Bolaños et al., 2013), but for active labeling) by a RBF-SVM classifier trained on CNN features to distinguish 'Object' vs. 'No Object' instances.

The easiness measure seems a promising method for obtaining object candidates, in general. However, this technique does not obtain the same results in egocentric datasets due to the fact that images are not captured by a person looking at objects of the world, but are acquired non-intentionally while a person is loosely wearing the camera. Due to the inherent low frequency of appearance of different objects of the real world, to the limited image quality of the wearable egocentric devices and to the constant moving of the user, a great part of the photos are unclear, dark or blurry (see Fig. 1). All this causes lower precision, when clustering the obtained object candidates.

**Refill strategy:** In order to solve this problem, we define a "refill" methodology as follows: at each iteration, the set of selected easiest samples is completed with a certain percentage (w.r.t. the number of easy samples retrieved) of randomly chosen labeled samples distributed on the already discovered object classes. In this way, we address two problems: 1) difficulty to form a cluster from a very small set of class instances, and 2) difficulty to link samples of the same class that were blurry and unclear. So, refilling the space with more samples of the same class of objects, we can obtain more compact clusters (see Fig. 3 and Fig. 4).

![Fig. 3. Clusters formed by the easiest samples.](image1)

![Fig. 4. Clusters formed by the refilled easiest samples.](image2)

### 2.2. Features for Object Discovery

As features to cluster the object candidates, we used a pre-trained CNN (Krizhevsky et al., 2012), which captures information about millions of images in a succession of convolutional and pooling layers. We deleted the last layer, which offers a supervised classification in 1,000 ImageNet classes, and used the output of the penultimate layer as our features (4096 variables). Note that our approach is different to the one of (Lee and Grauman, 2011) that used: LAB histograms for extracting colour information, Pyramid HOG for extracting shape information, and Spatial Pyramid Matching (Lazebnik et al., 2006) for extracting texture information.

### 2.3. Object Discovery

After the features are recovered for the easiest and the refilled instances on each iteration, we apply an Agglomerative Ward clustering on the object candidates, where we used as cutoff clustering criterion $cutoff = 2\sigma^2 + \mu$, being $\sigma^2$ and $\mu$ the standard deviation and the mean of all the distances between the clusters in the resulting hierarchy. Moreover, once the clusters are formed, we get the Silhouette Coefficient (Tan and Stein-bach, 2011) on each cluster and select the best for the user to assign it a label (Lee and Grauman, 2011). This coefficient is only calculated on the unlabeled samples, never using the refilled ones for selecting the most reliable cluster.

At the end of each iteration, a OneClass-SVM (with $\nu = 0.1$) for searching for harder instances is built with the new cluster and the rest of the easy samples are classified (Lee and Grauman, 2011). In any case, the refilled samples, which were already labeled, can only change their labels, if did not belong to the initial bag of refill.

### 3. Results

In this section, we discuss the three datasets we used (summarizing their characteristics in Table 1), and expose the different tests applied to illustrate the EOD performance.

#### 3.1. Datasets

Due to the low number of publicly available egocentric datasets and the complete lack of egocentric object-labeled datasets, we considered very important to construct one and make it public in order to serve as a base for algorithms comparison for the egocentric community.

The Egocentric Dataset of the University of Barcelona (EDUB) (see Fig. 5) is a dataset composed of 4912 images acquired by 4 people using the Narrative wearable camera (www.getnarrative.com). It is divided in 8 different days, 2 days per person. The objects appearing in the images are segmented (although here we only use their bounding box) and their annotations are similar to the ones provided by PASCAL. EDUB includes the following classes (number of samples per class are given in parenthesis): 'lamp' (2299), 'tvmonitor' (1274), 'hand' (1232), 'person' (1175), 'glass' (831), 'building' (732), 'face' (565), 'aircon' (530), 'sign' (506), 'cupboard' (392), 'paper' (377), 'car' (315), 'bottle' (260), 'door' (199), 'chair' (179), 'mobilephone' (145), 'window' (138), 'dish' (65), 'motorbike' (64), 'bicycle' (12), and 'train' (4). Note that in our tests, we did not use the classes with few instances (i.e. smaller than 100), considering that it would not be possible to discover them with a clustering strategy.

The second of the datasets we considered is the PASCAL VOC 2012 (Everingham et al., 2012), being one of the most widely used in object detection/recognition research, with very difficult and challenging images. We used the 'trainval' (for having more samples) set of images for our tests, but previously deleted the images that had in common with its 2007 version. We applied this pre-processing to avoid any bias in the results, since some of the used object detection methods were trained using PASCAL VOC 2007.
The last of the datasets, we chose is the **Microsoft Research Cambridge (MSRC)** (Lee and Grauman, 2005), which was also used in (Lee and Grauman, 2011) for object discovery, and therefore will ease the comparison of the results. Considering that MSRC dataset is labeled at pixel level, we had to extract the bounding boxes corresponding to each of the objects making some assumptions: 1) the bounding box for an object is the minimal closing box around all the connected pixels that belong to the same class; 2) given the dataset is split in folders, we only considered valid the objects with the same class as the folder’s name; 3) the minimal area for an object to be valid was set to 50x50 image pixels (about 0.81% of the whole image); and 4) we excluded the labels ‘grass’, ‘sky’, ‘mountain’, ‘water’ and ‘road’, because they are not objects, but rather environments.

Fig. 5 shows some image samples from the 3 datasets. MSRC dataset, compared to the other two should obtain better results due to the position of the objects (central to the image) and their clear appearance. Even though in general PASCAL has some object instances very difficult to find, the hardest one (also considering the high rate of objects occlusions, blurriness and low image quality) is the EDUB.

### 3.2. Object Detection Methods

Given that the first step of the algorithm is to obtain object candidates from the images, we tested and compared four different state of the art object detection methods on the three datasets (see Table 2). We chose Objectness (Alexe et al., 2010), BING (Cheng et al., 2014), Multiscale Combinatorial Grouping (MCG) (Arbelaez et al., 2014) and Selective Search (Uijlings et al., 2013) methods considering their good performances. For MCG, we applied its quickest, but less exhaustive version.

Due to the dramatic increase of space needed to store all the samples 1 we extracted the top $W = 50$ object candidates per image sorted by their objectness score.

Analyzing the percentage of NO (see overlapping score in section 3.3) and DR of each method, we can see that the DR is not as high as desired and the % of NO is remarkably high. Meaning that using any of the best state of the art approaches for object detection makes us lose a lot of information, so we have to consider that our final results will be inevitably biased and worsen for this reason.

Comparing the different datasets, as one could immediately expect looking at the images, it is clearly easier for any objectness measure to get good results on the MSRC dataset, meanwhile it is quite more difficult on PASCAL and EDUB, having an extra difficulty for the second one due to the non-intentional acquisition and less clear images of the wearable cameras.

Given our final goal of being able to discover the true distribution of object classes and as many individual Ground Truth (GT) objects as possible, we considered that the objectness measure that obtained better results for EOD was the one proposed by (Alexe et al., 2010), because we are interested in getting most of the GT objects in the dataset, even if we have to deal with a lot of NO (i.e. noisy or FP) instances.

### 3.3. Test Settings

In order to perform the algorithm validation, we first **leave a 50% of the object classes in the unlabeled pool** as a test set. Note that we need to test if the algorithm is able to discover unseen object classes. From the remaining part of classes, similar to (Lee and Grauman, 2011), we separated a 40% of the total object candidates to represent the initial knowledge located into the bag of refill and used the remaining 60% for testing, too.

In order to say that a candidate matches a GT object bounding box, we followed the PASCAL VOC challenge criterion, that uses the Overlapping Score (OS). A GT label is considered a

**Table 1. Image/object characteristics for each of the used datasets.**

|       | images | object candidates | GT objects | classes |
|-------|--------|-------------------|------------|--------|
| **MSRC** | 3,427  | 171,350           | 4,217      | 16     |
| **PASCAL** | 16,369 | 818,450           | 38,144     | 20     |
| **EDUB** | 4,912  | 245,600           | 11,149     | 17     |

**Table 2. Percentage of ‘No Objects’ (NO) and Detection Rate (DR) comparison of the four object detection methods on our three datasets.**

|       | Objectness | BING | MCG | Sel.Search |
|-------|------------|------|-----|------------|
| **MSRC** |            |      |     |            |
| NO    | 91.69      | 96.68| **48.42** | 61.95      |
| DR    | **88.33**  | 64.15| 79.61| 70.98      |
| **PASCAL** |            |      |     |            |
| NO    | 92.14      | 92.93| **65.16** | 71.30      |
| DR    | **60.47**  | 56.93| 49.36| 36.71      |
| **EDUB** |            |      |     |            |
| NO    | 92.75      | 95.43| **79.17** | 84.27      |
| DR    | **60.45**  | 50.00| 49.57| 29.09      |

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1Considering the PASCAL 12 dataset, we needed nearly 30GB of data to store all the images and features for the tests.
hit, iff:

$$OS = \frac{|GT \cap \omega|}{|GT \cup \omega|} > 0.5,$$

(1)

where \(\omega\) stands for the window region detected by the object detector. Due to the challenging images presented to the object detector, a very high percentage of samples (more than 92% using Ferrari’s objectness) could not be considered objects, and were labeled as NO.

In order to tune the parameters for the SVM filter strategy for each of the datasets, we applied a nested 5-fold cross-validation with 5 test divisions with a grid of parameters of \(\sigma \in \{0.1, 0.5, 3, 10, 100, 1000\}\) and \(C \in \{0.1, 0.5, 3, 10, 100, 1000\}\). All the tests were performed for each dataset separately, on a randomly selected fraction of its samples to save computational time. With these tests, we finally found that the best parameters for filtering as many NO instances and at the same time keeping as many ‘Object’ instances as possible (high sensitivity and high specificity) for both the PASCAL and the MSRC classifiers were \(\sigma = 100\) and \(C = 3\). In the labeling step, for simulation purposes, we labeled the best cluster with a majority voting strategy w.r.t the GT, although this labeling is intended to be made by the camera user himself/herself.

We designed different test settings to evaluate our proposal:

S1: Features of (Lee and Grauman 2011).
S2: CNN object features.
S3: CNN object features with Refill strategy.
S4: CNN object concatenated with CNN scene features and Refill strategy.
S5: CNN object features with Refill and SVM filter.
S6: CNN object features with Refill, SVM filter and PCA.

With the first pair of settings, we intend to compare the generalization capabilities of the appearance features from (Lee and Grauman 2011) against the extracted CNN features. In setting S4, we tested adding a context about the scene, and in setting S6, we applied a PCA feature dimensionality reduction and transformation in case there is redundancy in the extracted CNN features.

3.4. F-Measure Comparison on EDUB

To evaluate our approach, we used the F-Measure, because it objectively penalizes the FP and FN objects in each class, that is, represents a trade-off between the Precision and Recall of the method. At the same time, we want to give the same importance to all classes, and are interested in finding as many different classes as possible, but always leaving the NO instances aside, without considering them into the quality measures. Hence, we applied the average per-class precision and recall defined in (Sokolova and Lapalme 2009) in order to obtain the average F-Measure:

$$\text{F-Measure} = \frac{2 \cdot \text{Precision}_M \cdot \text{Recall}_M}{\text{Precision}_M + \text{Recall}_M},$$

(2)

where \(\text{Precision}_M\) and \(\text{Recall}_M\) are the mean precision and recall of all classes, giving the same weight to all of them.

All measures were averaged by at least 5 executions per setting and for a maximum of 100 algorithm iterations. Using these tests, we compared all settings at the end of the easiest samples discovery (Fig. 7) and the F-Measure for all settings on each iteration (Fig. 8).

Looking at Fig 7, we can clearly see that using CNN outperforms the features of (Lee and Grauman 2011), indicating that they can form purer clusters and find a wider variety of classes thanks to their best representation. Then, adding the Refill technique, the EOD method outperforms the one using the CNN features only, which proves the assumptions made in section 2.1. The rest of the methods can not reach the same results as CNN + Refill. Moreover, using the additional CNN features of the whole image adds just noise to the set of features. That is, simply by using the CNN with the bounding box of the object candidate already captures the closest and most relevant object context. Considering the high dimensionality of CNN features, it seems that including a PCA dimensionality reduction to the data does not provide any benefit to the object discovery.

Comparing the evolution of the F-Measure through the iterations (Fig. 8), we see that any of the settings using CNN features experiments a much higher increase in the F-Measure value just in the first 5-10 iterations, meaning that they can find clusters of true objects quicker than using the setting S1.

Hence, using the CNN features combined with the refill strategy, the results clearly improved from 0.072 to 0.285. This is caused by the discovery of different classes of samples. While when using the features of (Lee and Grauman 2011), we are only able to discover 3 or 4 classes at most, achieving an average of 0.072 F-Measure; with the setting S3, we can discover instances of more than half of the classes, getting nearly 0.29 of F-Measure. Although on the EDUB using the setting S5 (CNN + Refill + SVM Filtering) does not seem to get as good F-Measure results as on the other settings, in other datasets it outperforms or nearly reaches the results of setting S3. Furthermore, it gets a wider variety of object classes.

3.5. F-Measure Comparison on All Datasets

After having found the best combination of methods and parameters to use, we tested and compared how good the new method was contrasting it with the state of the art method (Lee...
and Grauman [2011] for any of the datasets (EDUB, PASCAL 2012 and MSRC). In table 3, we can see a summary of the F-Measure results obtained for each of the datasets and each of the best test settings (average on at least 5 tests per setting).

Table 3. F-Measure comparison for the three datasets, the state of the art (Lee and Grauman [2011]) and our best test settings (CNN + Refill and CNN + Refill + Filter).

|       | S1     | S3 (ours) | S5 (ours) |
|-------|--------|-----------|-----------|
| MSRC  | 0.121  | 0.431     | 0.410     |
| PASCAL| 0.002  | 0.145     | 0.179     |
| EDUB  | 0.072  | 0.285     | 0.250     |
| Average| 0.065  | 0.287     | 0.280     |

As we can see, using any of our best methods (either setting S3 or setting S5) clearly outperforms the state of the art features, having from a 350% to a 9000% of improvement depending on the dataset and the settings, and a 453% of average improvement with the best setting.

Even though the average F-Measure result obtained using the SVM filtering (setting S5) is worse than without it (setting S3), we must consider that these classifiers have been built with samples from different datasets than the ones on test (1/2 of the PASCAL samples for MSRC tests and all MSRC samples for both PASCAL and EDUB tests), meaning that the generalization will be poorer than if we built a general classifier with images from any of the datasets.

Another important consideration we must take into account, is that for the MSRC tests, although the final (after 100 iterations) F-Measure results are better without the filtering, in fact they were better with the filtering from the 1st to the 75th iteration, meaning that in some cases, it can offer better results if we want to stop early the discovery method.

3.6. Object Discovery Results

In this section, we analyze the object discovery results. In Fig. 9, we can see the absolute number of object instances found by each of the methods compared to the GT and the ones found by the Objectness measure ([Alexe et al.] 2010), in this case without counting repeated instances of the same object).

Fig. 9. Objects found by each method compared to the GT and the ones found by the Objectness measure ([Alexe et al.] 2010).

As we can see, using the parameters of setting S1 ([Lee and Grauman] 2011), we are only able to find instances from 3 different classes, which causes the previously seen very low F-Measure results. On the other hand, using either CNN + Refill (setting S3) or CNN + Refill + Filter (setting S5), we can clearly discover objects from a wider variety of classes, which also causes the higher resulting F-Measure. Moreover, we get a wider variety of classes with setting S5 (10 different classes) than with setting S3 (8 different classes).

If we check the discovery order of the classes in each of the methods (see Fig. 10), we can see that some classes are more easily discovered and repeated over the following iterations than others. This is caused not only by the number of class instances appearing in the dataset, but also by the previously acquired knowledge, the method used, and/or the intra-class variability.

Fig. 10. First discovery of the object classes as a function of iterations.

If we analyse the clusters number, where we find each class (see Table 4), we can see that even though having the same percentage of NO candidates (92.75%), using Grauman’s features (setting S1), we get 96% of the clusters labeled as NO, but only 71% of them using CNN + Refill (setting S3). Then, comparing it when adding the SVM filtering (setting S5), we can see that it gets reduced to a 49% of the clusters thanks to the dramatic reduction of NO instances in the pool of unlabeled samples.

In Fig. 11, we can see the evolution of GT unique instances discovered by each of the methods on the accumulated iterations (each data point corresponds to an algorithm iteration) w.r.t. the F-Measure obtained by the method. We can see that using Grauman’s features seems to cover a wider variety of object samples than either with settings S3 or S5 (about 16% against about 6.7% of the GT samples). This result is probably directly related to the lower F-Measure obtained. Due to the lower generalization and representation capabilities of the set of features used (compared to CNN), the labeled clusters
contain a wider variety of samples and objects, causing to label more unique object instances, but at the same time having a worse average result.

Regarding the complexity of EOD, it is easy to see that: a) the objectness score extraction is of complexity $O(N)$, being $N$ the number of images in the dataset; b) the SVM filtering has complexity $O(N)$; c) the sorting of easiest objects is $O(N \ast \text{Wlog}(N \ast W))$, being $W$ the number of candidates extracted for each image; d) the refill strategy is $O(1)$; e) the CNN features extraction is $O(M)$, being $M$ the easy objects number in the current iteration; f) the clustering of easy objects is $O(M^2)$; g) the best cluster labeling is $O(1)$; h) the one-class SVM cost is $O(M)$, leading in total a cost of $O(N \ast \text{Wlog}(N \ast W) + M^2)$, for each iteration.

### 4. Conclusions and future work

In this paper, we proposed a novel semi-supervised object discovery algorithm for egocentric data that relies on features extracted from a pre-trained CNN and uses a refill strategy for finding easily the classes with less samples. Moreover, we added a SVM filtering strategy for discarding a great part of the high amount of ‘No Object’ classes produced by any of the objectness measures. We compared 4 of the state of the art objectness measures in terms of ‘No Object’ instances produced and the Detection Rate acquired when extracting a low number of object candidates ($W=50$). We proved that the CNN features, the refill strategy (and the SVM filtering) can produce much better F-Measure results and can discover a larger number of infrequent classes than the state of the art approach on three datasets (MSRC, PASCAL 12 and EUBDB), either being from general easy images, to egocentric and very difficult ones.

Furthermore, we proved that this combined strategy also works better than the previous ones for very noisy and blurry images.

Our future work involves the following tasks: 1) Define an algorithm to discover objects, scenes and people to characterize the environment of the persons wearing the camera, 2) Propose an iterative scene and object discovery to take profit of the samples discovered from the complementary categories, and 3) Make the method discriminative i.e. to detect which are the objects and scenes that characterize the environment of a person and distinguish them with respect to those of the other people.

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