Bandwidth limited object recognition in high resolution imagery

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Abstract

This paper proposes a novel method to optimize bandwidth usage for object detection in critical communication scenarios. We develop two operating models of active information seeking. The first model identifies promising regions in low resolution imagery and progressively requests higher resolution regions on which to perform recognition of higher semantic quality. The second model identifies promising regions in low resolution imagery while simultaneously predicting the approximate location of the object of higher semantic quality. From this general framework, we develop a car recognition system via identification of its license plate and evaluate the performance of both models on a car dataset that we introduce. Results are compared with traditional JPEG compression and demonstrate that our system saves up to one order of magnitude of bandwidth while sacrificing little in terms of recognition performance.

1. Introduction

The explosion in mobile phone ownership has made taking and sharing pictures commonplace in our daily lives. Average smartphones capture 10 megapixel images, and high-end smartphones capture up to 20 megapixel images. Such high resolution images provide detailed information on the objects in the scene, which are only appreciated after zooming into these regions. For example, Figure 1 shows the same image at two different resolutions. On the left, the upper image corresponds to the original image with its original 16 megapixel resolution. On the right, the top image corresponds a downscaled version of the image – in this case 640×480 pixels (0.30 Mpixel). This is a common resolution used in computer vision and almost the highest resolution that can be fed into state-of-the-art convolutional neural networks. At first glance both images look fairly similar. However when zooming in, the original resolution image preserves information valuable for performing tasks such as face recognition or license plate transcription, while the lower resolution image has completely lost that information. In this article we investigate the detection of objects in high resolution imagery for bandwidth critical applications. We focus on objects which are structurally related to others (like license plates with cars, and faces with persons).

Low bandwidth communication is important for all applications where computation is performed at the server-side. For such applications reducing the amount of transmitted data is crucial for the speed of the application and to reduce costs. This is especially true when considering...
satellite communications which are used extensively in situations where standard phone networks are absent (e.g. fire detection with drones), in emergency situations when there is a sharp increase in call volume and terrestrial network capacity is saturated (or absent due to a disaster) or in high security situations where satellite communications is more secure [10][12]. The objective of this work is to improve the efficiency of visual communication in bandwidth-limited scenarios. Our emphasis is on conserving total pixels inspected (and thus transmitted), rather on end-to-end computational efficiency. Especially in satellite communications, where bandwidth costs can be as high as $1 per megabyte, it is more critical to reduce bandwidth consumption and rather than optimizing computational efficiency.

Image compression is a standard approach in the communications field when it is necessary to cope with bandwidth limitations and costs. These techniques exploit the highly correlated nature of natural images [15][16]. However, this practice, besides reducing the bandwidth needed to send the image, also reduces the information contained, which in some cases may result in critical information losses. To obtain superior bandwidth reduction, some applications resort to human operators who interactively and progressively request higher resolution of regions of interest from a low resolution image. As such, they discard large parts of the image which are considered redundant for the task at hand. In this paper we propose a method for Multi-stage object detection in which we maintain the computation and bandwidth benefits of working with low resolution images while keeping the valuable information that is contained in the original image.

Object recognition has seen significant changes over the last decade. It has long been dominated by sliding window approaches [2][8]. An alternative approach is based on object proposals which reduce the number of windows considerably thereby allowing the use of more complex classifiers [7][14][17]. The breakthrough in deep convolutional networks, which first showed remarkable results on image classification [8], was almost immediately extended to object proposal methods, and has resulted in a considerable performance improvement for object detection [5]. Several papers have further improved these results and increased speed [3][11]. As a result of these improvements the accuracy of object detection greatly improved, and these techniques can now be used as reliable building blocks in computer vision pipelines.

Actually, detection in high resolution images has received relatively little attention – the fast growth of image size in commercial cameras seems to have gone unnoticed by the object detection community. Most research has focused on detecting relatively large objects in low resolution images. In fact, popular state-of-the-art object detection algorithms based on convolutional neural networks (CNN) cannot handle high resolution imagery, for example, the popular AlexNet [8] rescales all images to a meager \(224 \times 224\) pixels (0.05 megapixels) before processing. As discussed before this resolution reduction comes at the cost of losing valuable information, which in turn results in an inability to detect or recognize all objects present in the image.

The image interpretation process needed for interactive, low bandwidth image communication is traditionally done by humans, which is costly and slow. We propose to apply object recognition to automatically identify the relevant regions in images. We call our approach active information seeking because it mimics the actions a human operator would perform in order to actively identify semantic objects while consciously and actively limiting the bandwidth consumed. We investigate two approaches for the active information seeking for objects which are structurally related to others (like license plates with cars, and faces with persons).

Firstly, we propose a Multi-stage approach which identifies promising regions of interest in low resolution imagery and progressively requests the regions in higher resolutions to perform recognition of higher semantic quality. Secondly, we propose a direct-estimation approach which detects objects (e.g. cars) in images and directly estimates the location of their parts (e.g. the license plate). This allows to directly extract the part at a higher resolution, thereby further reducing bandwidth usage.

This paper is organized as follows. In the next section we describe a framework for Multi-stage recognition models that allows us to quantify bandwidth savings of one model versus another. In Section 3 we present our approaches for bandwidth-limited object recognition. Then, in Section 4 we report on a number of experiments we performed to quantify the performance of our approach with respect to baselines and the state-of-the-art. Finally, we conclude with a discussion of our contribution in Section 5.

2. A framework for bandwidth-limited recognition

In this section we describe our architecture for bandwidth-limited recognition in high resolution images. Our approach is based on actively selecting which parts of the image to inspect at higher resolutions. This allows our system to save bandwidth by ignoring semantically irrelevant portions of images. The model takes a low resolution image from which consecutive requests of higher resolution regions are made to extract the desired information. This model can be applied to detect semantic objects contained in a sequence of objects of decreasing size. For example, the license plate is contained in the image of the car, which is itself contained in an image of a street scene. With our approach, we can access high resolution images of such objects without having to inspect the entire image at high
resolution. This model can be applied to an interactive visual communication system for bandwidth limited channels where images are first sent in low resolution and then parts of it can be requested in higher resolution, this allows large amounts of savings in bandwidth with no sacrifice on details which may be relevant.

Our object recognition framework is illustrated in Figure 2. We use a Recursive model of information seeking that identifies promising regions to inspect at increasingly higher resolutions. In this figure, \( I_j^i \) stands for the \( j \)-th subimage inspected at the \( i \)-th level of resolution. Subimages at level \( i \) are all of the same size of \( n_i \times m_i \) pixels. At each level \( i \) of the model, \( N_i \) subimages are inspected at \( n_i \times m_i \) pixel resolution.

The system begins with the original image \( I_0^0 \) at low resolution as input. A detector (or some other method to identify promising subimages) is then applied. The detector detects \( N_1 \) regions of interest, e.g. cars if our final goal is to identify license plates. Each of these subimages is then inspected at stage 1 of the model, and a total of \( N_2 \) regions of interest are passed to stage 2 for inspection at higher resolution. This process is repeated \( n \) times, where \( n \) varies depending on the application. Finally, the desired information is extracted from the last sequence of subimages.

Following this notation, the cost of inspecting the sequence of images is:

\[
\text{Cost} = \rho \sum_{i=0}^{n} N_i \cdot n_i \cdot m_i, \tag{1}
\]

where \( \rho \) is a constant representing the bandwidth in MB needed to send one pixel. Our final goal is to have a final cost much lower than the cost of inspecting the image for the desired objects of interest at its original high resolution.

3. Two models for bandwidth limited recognition

In this section we propose two different models for bandwidth limited object recognition. The first is based on Recursive application of the Fast-RCNN detector [4]. Then, in Section 3.2 we describe a second approach based on simultaneous estimation and localization of regions of interest and high-resolution objects contained in them.

3.1. Recursive Fast-RCNN

To select the regions which will be requested at higher resolution we use the Fast-RCNN object detector [4]. Fast-RCNN was originally proposed to directly detect objects from a single resolution of an input image.

The Fast-RCNN detector. Assume there are \( C \) object classes we wish to both recognize and localize in images. A trained Fast-RCNN network takes as input an image \( I \) and a sequence of \( R \) bounding box proposals:

\[
B = \{ b_i \mid i \in \{1, 2, \ldots, R\} \},
\]

where each \( b_i = (x_i, y_i, w_i, h_i) \) encodes the geometry of the \( i \)-th bounding box proposal. These proposals may be generated by Selective Search [14], Edge Boxes [17], or any bounding box proposal strategy one prefers [6].

The Fast-RCNN network then produces a structured output \( P \), which consists of two elements for each bounding box proposal in image:

\[
P = \left\{ p(c \mid b_i), \hat{b}_{i[c]} \mid i = 1, 2, \ldots, R \right\}.
\]

Each \( p(c \mid b_i) \) is the estimated probability that box \( b_i \) belongs to class \( c \). Each \( \hat{b}_{i[c]} \), on the other hand, is a refined bounding box prediction that adjusts the original proposed box geometry \( b_i \) (using visual information from \( I \)) to better predict the expected bounding box location and extent of a box from class \( c \). The final predicted class probabilities and boxes are computed using standard non-maximum suppression on \( P \).

Internally, the predictions of both \( p(c \mid b_i) \) and \( \hat{b}_{i[c]} \) are made on the basis of a visual representation of each box \( b_i \) extracted from neuron activations in intermediate layers of a CNN (typically the last fully-connected layer of the network). This is an essential feature of the Fast-RCNN framework: the convolutional features are computed over the entire image up to a pre-defined point in the network, then these features are pooled into the representations of each bounding box proposal in \( B \). These are then sent down
to the rest of the network which estimates outputs \( p(c|b_i) \) and \( b_{i,c} \).

A Fast-RCNN network is trained by optimizing an average per-box multitask loss over all training images. This multitask loss drives the network to both recognize and localize the desired object classes by simultaneously learning a classifier for all object categories and a regressor from bounding box proposals to boxes that (on the basis of visual content of the proposed bounding box) better fit the ground truth object box annotations. See [4] for complete details of this optimization procedure.

**Recursive application of Fast-RCNN.** In order to actively seek objects at high resolution, as described in the previous section, we require a Fast-RCNN detector that works at multiple levels of resolution. In this first model, we achieve this by applying Fast-RCNN Recursively. In our application, a car detector based on Fast-RCNN is first run, after which a second Fast-RCNN network trained to detect license plates is run on the selected car bounding boxes extracted at high resolution. Finally, an off-the-shelf OCR engine is used to recognize the text of each localized license plate.

### 3.2. Multi-stage network

The main objective of our framework is to perform object recognition and minimize the bandwidth needed, where bandwidth is measured in the total number of pixels inspected by the detector. In this section we propose a second model that saves even more bandwidth than the one proposed above. In this model, in addition to detecting an object of interest at each stage, we simultaneously predict the subregion which is likely to contain the object or objects of interest in the next stage. Thus, instead of requesting the entire object of interest from the previous stage (e.g. the entire car detection), we directly request a smaller region of interest for the next stage (e.g. a smaller region which is expected to contain the license plate). With respect to the Recursive Fast-RCNN model described in the previous section, this allows us to skip an entire Fast-RCNN stage and thus save more bandwidth. In the car recognition example, instead of requesting the cars at a higher resolution, at the second stage of processing we can directly request the license plates at higher resolution and proceed to the OCR stage.

To implement this Multi-stage model, we propose a novel network architecture. The proposed network has the same inputs as Fast-RCNN, an input image \( I \) and a sequence of \( R \) bounding box proposals. However, the output \( P \) produced for each bounding box proposal, contains four elements instead of two:

\[
P = \{ p(c|b_i), b_{i,c}, p(s|\hat{b}_{i,s}), \hat{b}_{i,s} | i = 1, 2, \ldots, R \},
\]

where \( p(c|b_i) \) is the estimated probability that box \( b_i \) belongs to class \( c \), \( \hat{b}_{i,c} \) corresponds to the refined bounding box prediction to the main object, \( b_{i,s} \) stands for a second regression done from the proposed bounding box which corresponds to the localization of the object which is to be detected in the next stage (the sub-object). Finally, \( p(s|\hat{b}_{i,s}) \), is the estimated probability that the bounding box from the second regression belongs to class \( s \).

The basic architecture of the network is similar to the Fast-RCNN network with the two different heads for the object class loss and the object bounding box loss (see Figure 3). In our Multi-stage network, we introduce another regression head to directly estimate the coordinates of the sub-object (the object to recognize at the next stage). In addition, we introduce a classification head to compute the sub-object classification score which can be used as a quality measure of the sub-object coordinates.

Directly estimating this sub-object classification loss in parallel with the other three heads was found to provide sub-optimal results. Therefore, we introduce an additional pooling layer to extract the features within the estimated bounding box of the sub-object. In order to obtain these features from the last convolutional layer an unnormalization layer is needed. This layer changes the coordinates of the estimated bounding box from being normalized with respect to the bounding box proposed by selective search to being normalized with respect to the whole image. In Section 4 we show that the output of the sub-object classification layer can be exploited when deciding on an additional margin to the bounding box of the sub-object to extract. When the sub-object classification score is high no additional margin is required. For low scores a large margin is used to ensure the sub-object is within the extracted region.

To train the network we minimize the sum of the losses over all ROIs and all training images. Specifically the loss of a single ROI has four components:

\[
L_{j} (P_{j}, GT_{j}) = L_{\text{cls}}^{\text{obj}} + L_{\text{cls}}^{\text{sub-obj}} + L_{\text{bbox}}^{\text{obj}} + L_{\text{bbox}}^{\text{sub-obj}},
\]

where \( P_{j} \) are the estimated outputs from the \( j \)-th ROI, and \( GT_{j} = \{ c_{j}^{GT}, s_{j}^{GT}, b_{j,c}^{GT}, b_{j,s}^{GT} \} \) is the ground truth of the object class \( c_{j}^{GT} \), the sub-object class \( s_{j}^{GT} \), and their ground truth bounding boxes, \( b_{j,c}^{GT} \) and \( b_{j,s}^{GT} \). The class loss is given by log loss of the true class:

\[
L_{\text{cls}}^{\text{obj}} = -\log p(c_{j}^{GT} | \hat{b}_{j}^{c}),
\]

\[
L_{\text{cls}}^{\text{sub-obj}} = -\log p(s_{j}^{GT} | \hat{b}_{j,s}).
\]

The location losses on the bounding boxes are defined as:

\[
L_{\text{bbox}}^{\text{obj}} = \begin{cases} \epsilon_{j} & \text{if } c_{j}^{GT} \geq 1 \end{cases} \text{smooth}_{L1}(\hat{b}_{j,c} - b_{j,c}^{GT}),
\]

\[
L_{\text{bbox}}^{\text{sub-obj}} = \begin{cases} \epsilon_{j} & \text{if } s_{j}^{GT} \geq 1 \end{cases} \text{smooth}_{L1}(\hat{b}_{j,s} - b_{j,s}^{GT}).
\]
where the Iverson bracket indicator function \([c^j_{GT} \geq 1]\) is one if \(c^j_{GT} \geq 1\) and zero otherwise. For bounding boxes which do not have a ground truth object because they are on the background \(c^j_{GT} = 0\) and \(s^j_{GT} = 0\) and the localization loss will be zero. The smooth L1 distance is used as a measure of the error

\[
\text{smooth}_{L1}(x) = \begin{cases} 
0.5x^2 & \text{if } |x| < 1, \\
|x| - 0.5 & \text{otherwise}.
\end{cases}
\]

There exists some related work which directly aims to regress to part (sub-object) coordinates. Liang et al. [9] first detect persons and then train a network to regress to the parts (clothes) given the detected person. Other than our method they separate the object detection and part detection. Cervantes et al. [1] propose a method which regresses directly to the object and parts. However, their approach only applies to images where a single object is present in the image.

Compared to the Recursive Fast-CNN of Section 3.1, the Multi-stage model we propose here allows us to skip one stage and therefore inspect fewer pixels and reduce bandwidth consumption. However, this could potentially come at the cost of performance loss because the regression to the sub-object bounding box coordinates is done from the low resolution input image.

### 4. Experimental results

In this section we report on a series of experiments performed to quantify the performance of our approach in terms of recognition accuracy and bandwidth savings. We first introduce a new car recognition dataset we collected to evaluate our two models.

#### 4.1. A dataset for car recognition

Car datasets often cannot be used for license plate detection and recognition because the average car resolution is too low, while license plate datasets usually do not contain the full car. Consequently, most car or license plate datasets focus on one of the two problems, and rarely on both. Because of this, we introduce a new dataset for benchmarking car detection, license plate detection, and license plate recognition.\(^1\)

The dataset consists of 500 images taken on different days, with different devices, at different times and in different cities. All images have been manually annotated with bounding box coordinates of the car and the license plate, and the characters of the license plate were transcribed (when legible). Due to the variability in difficulty, all the annotations include a measure of its difficulty as “Easy”, “Medium” or “Hard”. This difficulty was determined considering occlusions, size and definition of the object. In Figure 4 we show some examples of images from the dataset with their corresponding difficulty annotation.

#### 4.2. Car recognition in high resolution imagery

We consider the task of car recognition in high resolution imagery as a practical application of the framework that we propose. By car recognition we mean recognition of its license plate since it is a unique way of identifying a car. Therefore, the final goal of the system is to read the characters of the license plate of all cars present in an image. License plate characters are normally relatively small with respect to the whole image and therefore not visible in a low resolution version of the image (see again Figure 1). However, since we know that the characters are going to be inside a license plate and the license plate at the same time will be contained in a car we can apply the models we proposed in Section 3. Both systems were trained on 75% of the images from the dataset proposed in Section 4.1 and tested on the remaining 25%.

For the Recursive Fast-RCNN model, we trained a car detector by finetuning a Fast-RCNN detector based on the VGG_CNN_M_1024 network.\(^2\) The license plate detector for the second Fast-RCNN network was trained on the regions of the training set containing cars. When testing the system, we pass the original images at low resolution to the car detector and select detections with a score of 0.3 or higher for inspection at higher resolutions by the license plate detector. Since we know that a car only contains one license plate, instead of considering all the license plate detections with a 0.3 score or higher we only consider the detection with highest score greater than 0.3. Finally, the region detected as a license plate is requested at higher resolution and passed to the Tesseract OCR engine.\(^3\) More details about the resolutions used at each are given in Section 4.3.

For the Multi-stage model, we trained the network proposed in Section 3.2 with a car detector and a license plate

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1. The dataset will be released upon publication of this work.
2. https://github.com/rbgirshick/fast-rcnn
3. https://github.com/tesseract-ocr/tesssrc
Figure 3: Diagram of the proposed Multi-stage network. The yellow box corresponds to the original image fed to the network, the blue boxes correspond to convolutional layers, the purple ones to fully connected layers, and the red letters to different losses to optimize. The proposed network follows a similar structure as VGG1024 up to the fully connected layer fc7, from which we have added extra layers to enable sub-object detection and localization.

![Diagram of the proposed Multi-stage network.](image)

Figure 5: Experimental results. (a) Car and license plate recall and character accuracy on the test fold with respect to the size of the image (in number of pixels on the longest edge) for the model 2. (b) 

(a) Recursive Fast-RCNN  
(b) Multi-stage Network

estimator. We consider all car detections with its corresponding license plate estimation with a score of 0.3 or higher. License plates are very small objects with respect to the entire image, and especially with respect to the resolution of the final convolutional layer in state-of-the-art networks. Consequently, estimation of the license plate position at such low resolution is not very precise and we add some margin to the estimation in order to ensure that the license plate is contained in that region. The margin $M_g$ added to the estimation is proportional to the estimated probability $p(s|\hat{b}_{ij}|s)$ that the predicted region contains the license plate. Indeed, we define $M_g$ as follows:

$$M_g = 1 - p(s|\hat{b}_{ij}|s).$$

The final predicted bounding box is computed by adding this margin to the predicted bounding box from the network, constraining it to be contained in the object bounding box from the previous level. Then, a license plate detector similar to the one used for the first model is run on the prediction of the license plate location. Finally, the license plate region is passed to the Tesseract OCR at high resolution for the final recognition.

4.3. Experimental evaluation

An important parameter is the optimal resolution at which the successive images should be processed. For the Recursive Fast-RCNN model we must decide the resolution of the original image at which the car is detected, the resolution at which to request the car to perform license plate detection, and finally the resolution at which to request the license plate before passing it to Tesseract. For the Multi-stage Network model, instead of determining the resolution of the car we have to request the estimation of the license
plate localization.

In order to determine these parameters we divided the training set into two folds; we used 75% of the training images to train the model and the other 25% of images for parameter crossvalidation. Considering the Recursive Fast-RCNN model, in Figure 5(a) we show the recall of car and license plate detection and character accuracy for different image resolutions. Car detection recall keeps increasing up to 500 pixels and then stabilizes. For license plate detection, there is a clear peak at 300 pixels on the longest edge of the car image, then recall stabilizes. Based on these results, we set the resolution of the original image to 500 pixels and of the car image to 300 pixels. We found OCR performance to keep increasing with resolution and therefore we use all available resolution for character recognition. Taking now into account the Multi-stage network model, in Figure 5(b) we show similar experiments where we determine to use 600 pixels on the longest edge for the original resolution in order to have a good car detection and license plate regression and 200 pixels on the longest edge for the license plate location estimation.

Our proposed framework is not only useful for optimizing bandwidth, but also to increase performance. This is shown in Figure 8, where we demonstrate the improvement in performance that the Recursive Fast-RCNN model yields with respect to training a neural network to directly search for license plates. The single stage approach has a considerably lower precision-recall curve. The difference is remarkable; using an active seeking approach prevents detection of false-positives where no cars exist, and knowing the car position provides important information on plausible license plate locations. In Figure 8 we show an example of the output from a network trained to directly detect license plates without previously detecting the car.

### 4.4. Baseline comparison with image compression

The objective of our paper is to use semantic classes to reduce the bandwidth required for recognition. This is a type of semantic image compression, and to the best of our knowledge there is no prior work on task-specific image compression. As a baseline we consider a system that compresses using JPEG and/or image resizing. Both operations reduce the bandwidth required to transmit the data. However, they also may negatively impact OCR character recognition performance. Our baseline system based on image compression is endowed with perfect license plate detection (i.e. we use the groundtruth license plate boxes). We evaluate OCR performance for five different resolutions \(R = \{500, 1000, 1500, 2000, 3000, 4000\}\), and eight different levels of JPEG compression quality \(Q = \{1, 5, 10, 15, 20, 25, 50, 75\}\). This leads to 40 possible pairs of image resolution and compression quality whose performance as a function of the cost (in log-megabytes, see Section 2) on the test set is plotted as orange points in Figure 7. The results of the Recursive Fast-RCNN are plotted as a yellow dot and the Multi-stage network as a green one.

As shown in Figure 7, both the Recursive Fast-RCNN and the Multi-stage network yield significant savings in terms of cost when compared to the JPEG model with an equivalent accuracy. The Recursive Fast-RCNN model re-
duces the cost over one order of magnitude and still reaches 64% character accuracy which is only 1% lower than the 65% character accuracy obtained by the JPEG baseline when sending the image at its original resolution. The Multi-stage Network is able to decrease the cost by 20% with respect to Recursive Fast-RCNN from an average of 0.073MB to 0.58MB. Pixel-wise, the Recursive Fast-RCNN framework requires the inspection an average of 18.6% of the pixels while the Multi-stage Network inspects an average of 17.6% of the pixels. This comes at a cost of 5% loss in character accuracy. This drop in accuracy is caused by the low resolution at which we are detecting small details from the image. However, we believe that the network could be improved by training over a bigger dataset.

When making the comparison between the proposed framework and the JPEG baseline, we stress that we have given the JPEG baseline algorithm the advantage of perfect car and license plate detection, while our framework must both detect and localize the license plate before recognition.

Figure 9 qualitatively illustrates the step by step execution of both proposed algorithms. Note that all the “Easy” cars and license plates are correctly detected (only one “Hard” car instance is missed).

5. Conclusions and future work

In this paper we proposed a framework for identifying promising regions in low resolution images and progressively requesting regions at higher resolution to perform recognition of a higher semantic quality. This framework is especially interesting to reduce the bandwidth needed in order to take advantage of all available resolution of modern high resolution cameras when recognizing objects. We propose two different models implementing license plate recognition within this framework. The first implementation consists of a Recursive Fast-RCNN model which uses a Fast-RCNN network at each level of the framework to perform object detection. The second model uses a Multi-stage Network to simultaneously localize and recognize both cars and their license plates at the first level of resolution, and thus allowing the network to inspect fewer pixels at subsequent levels.

Experimental results on both implementations show that the proposed framework yields significant savings in terms of bandwidth cost (measured with the number of pixels inspected for license plate recognition) when compared JPEG compression at an equivalent plate recognition accuracy.

The framework we propose is not incompatible with JPEG compression so as future work we would like to combine this framework with different JPEG compression levels to improve even further the savings in terms of bandwidth. Moreover, although the implementation of an OCR was not in the scope of this work, we would like to investigate in this field to improve the character accuracy.

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