

See the World through Network Cameras

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Abstract—Millions of network cameras have been deployed worldwide. Real-time data from many network cameras can offer instant views of multiple locations with applications in public safety, transportation management, urban planning, agriculture, forestry, social sciences, atmospheric information, and more. This paper describes the real-time data available from worldwide network cameras and potential applications. Second, this paper outlines the CAM² System available to users at <https://www.cam2project.net/>. This information includes strategies to discover network cameras and create the camera database, user interface, and computing platforms. Third, this paper describes many opportunities provided by data from network cameras and challenges to be addressed.

Index Terms—Network Camera, Computer Vision, Emergency Response, Urban Planning

1 OVERVIEW

The first network camera was, perhaps, deployed at the University of Cambridge in 1993 for watching a coffee pot [1]. Millions of stationary cameras (also called surveillance cameras or webcams in some cases) have been installed at traffic intersections, laboratories, shopping malls, national parks, zoos, construction sites, airports, country borders, university campuses, classrooms, building entrances, etc. These network cameras can provide visual data (image or video) continuously without human intervention. The data from some (but not all) cameras are recorded for post-event (also called forensic) analysis. This paper explores the opportunities for analyzing data streams from thousands of network cameras simultaneously. Real-time data may be used in emergency responses; archival data may be used for discovering long-term trends. Figure 1 shows several examples of visual data from network cameras. As can be seen in these examples, the content varies widely from indoor to outdoor and urban to natural environments. This paper considers analyzing the data from many heterogeneous network cameras in real-time. The paper describes:

- Section 2: Potential applications for real-time network camera data
- Section 3: The Purdue CAM² System, including the (1) discovery and retrieval system for network cameras, (2) metadata collection details, (3) web user interface to visualize the locations of the cameras and recent snapshots, (4) system architecture to support real-time data analysis, and (5) resource manager to scale computational resources based on needs
- Section 4: The opportunities and challenges faced when utilizing data from network cameras

Network Cameras

There is no universally accepted definition of *network cameras*. This paper adopts the following definition: a network camera is connected to a network (the Internet or intranet) and can capture visual data automatically and indefinitely without human effort. A network camera may have movement (or pan-tilt-zoom, PTZ) capability. The cameras may send video streams continuously, take periodic snapshots, or acquire data when events are triggered (such as motion detection). Most network cameras are stationary; i.e., their locations are fixed. It is also possible to have mobile network cameras; some cruise ships take periodic snapshots of oceans and transmit the data through satellite networks. Some dashcams have network interfaces and may transmit data while the vehicles are moving or parked.

2 POTENTIAL APPLICATIONS

Analyzing visual data (image or video) has been an active research topic for decades. Historically, researchers analyze the data taken in laboratories. In

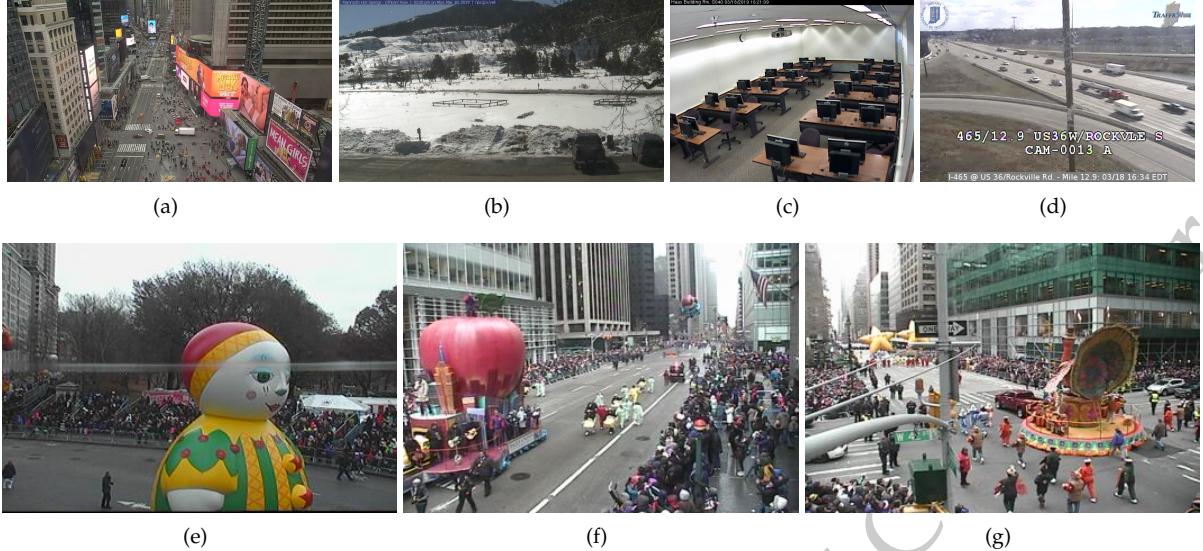


Fig. 1. (a) New York City. (b) Yellowstone National Park. (c) A computer lab. (d) I-465 highway in Indianapolis. (e)-(g) Thanksgiving Day Parade in New York City. All visual data in this paper is obtained from the Internet and publicly available without a password.

recent years, media hosting services (such as Flickr, Youtube, and Facebook) make sharing visual data much easier. Researchers start using the data acquired from the Internet to create datasets, such as ImageNet [2] and COCO (Common Objects in Context) [3]. Most studies are “off-line”: the analysis is conducted long after the data has been acquired and there is no specific restriction on the execution time. Often, only pixels are available and there is no time or location information about the data. As a result, it is not possible to link the data with the “context”, such as breaking news or a scheduled event. Furthermore, these datasets do not differentiate data taken from city downtowns or national parks. One exception uses periodic snapshots to observe seasonal trends in environments [4]; the study considers low refresh rates (a few images from each camera per day). In contrast, this paper considers data at much higher refresh rates (video or snapshots every few minutes). Adding time and location information can have profound impacts on how the data can be used, as explained in the following examples.

2.1 Virtual Tour

The world bank estimates international tourists reached 1.2 billion in 2015. Nothing can replace the personal experience of visiting a place, enjoying the culture and the local food; however, the hassle of traveling can be unpleasant. Many tourist attractions install network cameras and provide real-time data, such as the Yellowstone National Park and the Na-

tional Zoo shown in Figures 1 (b). Through these cameras, it is possible to provide “virtual tours” to visitors. Moreover, it is also possible using network cameras to watch scheduled events. Figures 1 (e)-(g) show images taken in New York City during the Thanksgiving Day Parade in 2014.

2.2 Air Quality

The National Park Service (NPS) deploys network cameras monitoring air quality [5]. Each camera takes one image every 15 minutes and posts the image on the NPS web site. The data is archived and can be used to study phenology. The data can be cross referenced with other sources of data such as the archive of weather data (humidity, temperature, cloudiness) and rare events such as wildfire. In addition to these cameras deployed in national parks, many TV stations deploy cameras watching cities. These network cameras may also be used to assess the air quality in the cities.

2.3 Transportation Management and Urban Planning

Improving transportation efficiency is a significant challenge in many cities (Chicago, Houston, London, Seattle, New York, etc.). Network cameras are widely deployed at traffic intersections. Currently, the real-time data allows city officials to monitor traffic congestion. In the future, this processes could be automatically optimized based on the real-time traffic information provided by the network cameras. Figure 1 (d)

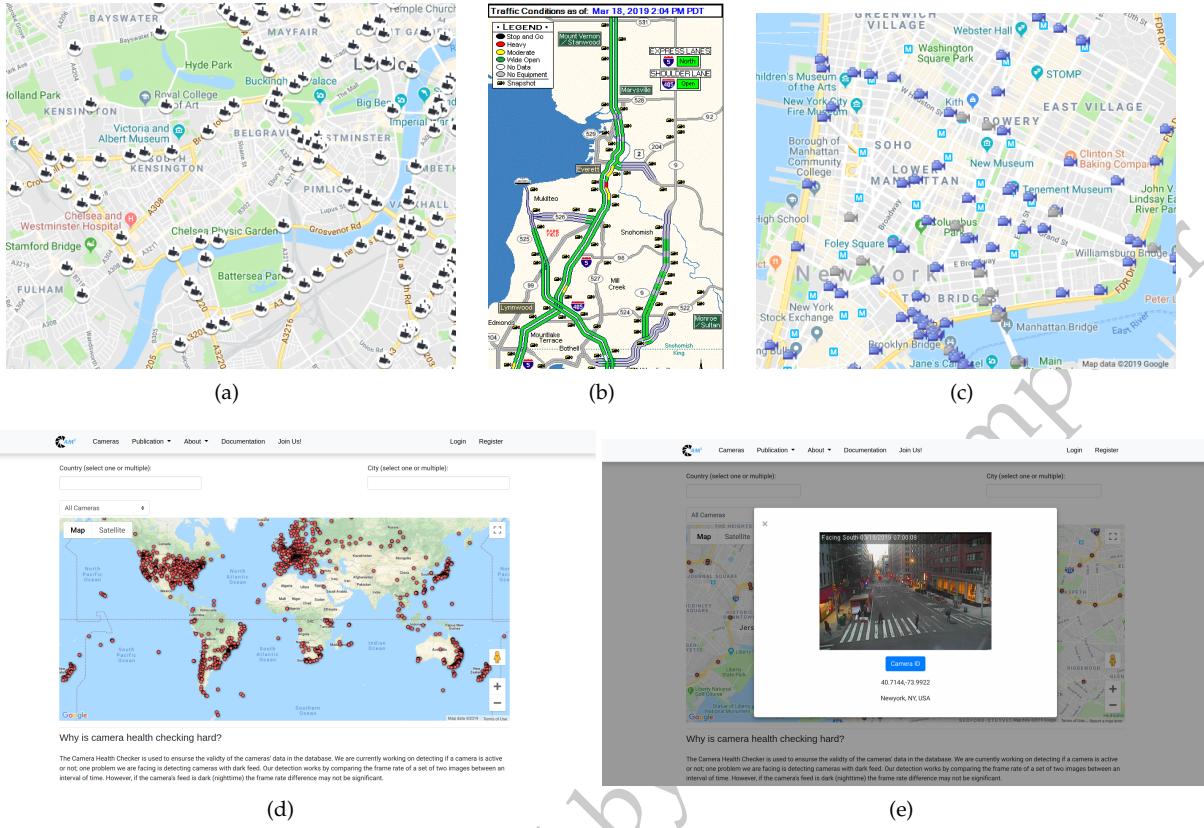


Fig. 2. Maps of traffic cameras in (a) London, (b) Seattle, (c) New York. Screenshots from the CAM² website (d) worldwide camera location map and (e) New York camera location map with one real-time image.

is an example of a traffic camera in Indianapolis. Figures 2 (a)-(c) show the locations of traffic cameras in London, Seattle, and New York.

2.4 Safety and Emergency Response

It is possible using network cameras to monitor large-scale emergencies. Figures 3 (a) and (b) show the flood in Houston on 2016/04/18. Since network cameras continuously acquire data, it is possible to conduct “before-after” comparison as shown in Figures 3 (c) and (d) when the highways returned to the normal conditions. Our recent study [6] suggests that data from network cameras can complement postings on social networks during emergencies. Network cameras continuously acquire and transmit data without human efforts; thus, network cameras can be used to monitor locations that have already been evacuated.

2.5 Human Activities

An experiment tracks the moving features in a video stream from a camera at Purdue University for 24 hours [7]. The experiment analyzes 820,000 images



Fig. 3. (a)(b) Houston Flood on 2016/04/18. (c)(d) Normal condition on 2017/02/14 taken by the same cameras.

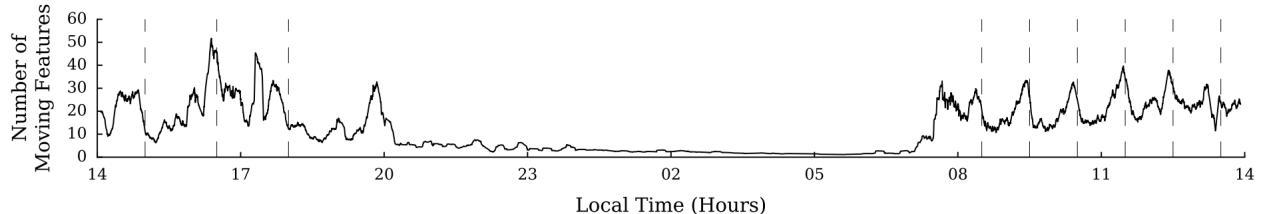


Fig. 4. Tracking moving features in a video stream of a camera at Purdue University. More moving features exist during the day, especially before the starting times of lectures (indicated by the vertical dashed lines).

(approximately 10 frames per second, FPS) from a single camera. Figure 4 shows that more moving features are detected during the day, especially before the lectures' starting times. This experiment demonstrates that it is possible to gain insights about the behavior of people using relatively simple analysis programs.

2.6 Versatile Data from Network Cameras

Computer vision has made significant progress in recent years. One factor contributing to the success is large datasets with thousands or millions of images and labels. Different datasets may have specific emphasis [8]. For example, images posted on social networks tend to have faces at or near the images' centers. Video captured by dashcams tend to have pedestrians at the horizon. Traffic cameras are usually 3-stories high looking downwards. These characteristics are a result of the sampling images from different data distributions. The difference among different datasets can be called "distinctiveness". Distinctiveness can be desirable because datasets focus on specific purposes—for face recognition, data from traffic cameras may not be useful. Data from network cameras provide a wide variety and is a rich source for data that is not always easily available in research laboratories.

3 CONTINUOUS ANALYSIS OF MANY CAMERAS (CAM²) PROJECT AT PURDUE UNIVERSITY

The previous section describes many examples where analyzing the data from network cameras (real-time images or video streams) can be helpful. This section describes a research project at Purdue University, CAM², to construct a system to continuously analyze visual data from many network cameras. Specifically, this section outlines how to discover network cameras from many different sources, retrieve data and metadata from them, the backend required for analyzing data in real-time, and a close inspection of the resource manager required for scaling computational needs of analysis programs.

3.1 Discover Network Cameras

IP and Non-IP Cameras

Many network cameras can be connected to the Internet directly and have unique IP (Internet Protocol) addresses. They are called "IP-cameras" in this paper. Some cameras (such as webcams) are connected to computers that make data available on the Internet. They are called "non-IP cameras" in this paper because the cameras themselves do not have own IP addresses. Each network camera may have an IP address but does not necessarily expose itself and may rely on a computer to act as a proxy. In this case, the IP address is the computer's IP address, not the camera's IP. Many organizations have web servers that show the data from multiple cameras. Since the IP addresses are the web servers' addresses, these cameras are also considered as non-IP cameras.

The applications described above require data from many geographically distributed network cameras. The procedure of finding network cameras and aggregation websites can be found in [9]. This article summarizes the process. IP-cameras usually have built-in web servers and the data can be viewed through web browsers. These cameras support HTTP (Hypertext Transfer Protocol). Different brands have different paths for retrieving data using the GET commands. Several methods can be used to find IP-cameras. One obvious method queries search engines. This method, however, has a low success rate because search engines usually return vendors of network cameras, not IP addresses of network cameras that can provide real-time data streams. Another method scans IP addresses by sending the GET commands of the known brands. If an IP address responds to the commands positively ("200 OK"), then the IP address becomes a candidate network camera. The candidate is further inspected by the Purdue team. Currently,

this process is manual for two reasons. First, some IP addresses respond to the GET commands even though they are not network cameras (false positive). Second, the Purdue team inspects the discovered camera and keeps it only if the camera data is from a public location (such as a traffic intersection, a park, or a university campus). CAM² is actively investigating the automation of discovering network cameras (c.f. Section 4.1). To automate privacy filtering in the future, we anticipate deep learning models may become capable of scene classification of private versus public locations.

3.2 Metadata Aggregation

Following network camera discovery, collecting additional information (called “metadata”) about the cameras is important (and possibly required) for data analysis. In this project, metadata includes (but is not limited to) the cameras’ locations, methods to retrieve data, the format of the data (such as MP4, flash, MJPEG, JPEG, and PNG), and the information about the refresh rate of the network cameras. Metadata may also describe the data’s content, such as indoor/outdoor, highway, parks, university campus, shopping malls, etc. Three particularly important pieces of metadata are location, data quality, and data reliability. These are explained in the following paragraphs.

Location information is required for many applications described earlier. In many cases, the owner of a camera provides the precise location (with longitude and latitude) of the camera. In some other cases, street addresses are given. It is also possible to use the IP addresses to determine the geographic locations but this approach may be inaccurate for several reasons. An organization (such as a university) may have a large campus. Knowing that an IP address belongs to this organization may not provide sufficient details about the camera’s location. Moreover, as mentioned above, some organizations show multiple data streams on web sites. The web servers’ locations do not reflect the cameras’ locations. In the future, accurate locations may be estimated by cross-referencing information from the network camera images with other resources. Some examples include (1) the time of day given the sunlight, the direction and length of shadow [10], (2) current events (like parades), and (3) identifying significant landmarks.

Data quality is critical for analysis. Data quality can be measured by many metrics. One is the resolution (number of pixels); another is the refresh rate (frames per second). The data quality may also be determined by the purpose of the applications: for example, if a camera is deployed to monitor traffic, then the data quality is determined by whether it can see congestion

clearly or the view is blocked by trees. In contrast, if a camera is deployed to monitor air quality, it is more important to evaluate whether the view has high visibility.

Reliability refers to the availability of the network camera data. For example, some network cameras only provide data during the daylight hours and do not provide data during night-time hours. Some network cameras are available 24 hours. Some others may be disconnected for various reasons, such as being damaged during a hurricane.

3.3 Web User Interface

CAM² is designed as an open research tool, available for other researchers to use. Thus, it has a web interface (<https://www.cam2project.net/>) for users to select cameras based on locations. Figure 2 (d) is a screenshot of the website. The locations of the cameras are shown as markers on a map (using Google Maps). When a marker is clicked, a snapshot is displayed, as shown in Figure 2 (e). The web site allows users to select cameras based on country, state (for USA.), and city. The map automatically zooms into the selected country. The markers in Figure 2 (d) were originally implemented using the Google Maps client API. However, as the number of cameras in CAM² grows, this is no longer a scalable solution. Experiments showed that loading 10,000 markers would take nearly 20 seconds for rendering the map. To improve scalability, the CAM² website uses Google Fusion Tables. This supports tile-based rendering of the markers on Google Map. The rendering time for 100,000 markers is less than 2.5 seconds.

3.4 System Architecture

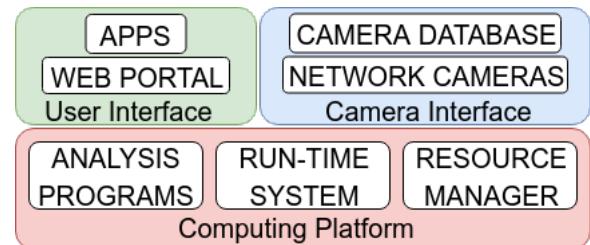


Fig. 5. CAM² has three primary components: User Interface, Camera Interface, and Computing Platform.

Figure 5 shows the three primary components of CAM² [11]: the user interface, camera interface, and computing platform. The user interface is made up of two access points. First, applications (Apps) can be programmed with our Python API (application

programming interface) [12] to access the CAM² system. Second, the user can access CAM² through a web portal. Aside from the user interaction, the entire CAM² system is automated. The web portal allows users to select the camera data streams for analysis, specify the desired analysis parameters (e.g., frame rate and duration), and submit the analysis programs. In other words, the web portal grants users access to the other two essential features of CAM².

The camera interface is accessed through the user interface. The camera database provides access to the network cameras. It is an SQL database storing the URL of the network cameras along with other metadata information. The network cameras themselves are, of course, already deployed globally. After or during data collection, the user can run an analysis program from the computing platform. For example, an analysis program can be used to track people (c.f. Figure 4).

The computing platform contains three major components, all of which enables users to run analysis programs on cloud servers. [12]. (1) Analysis programs are either created by users or selected from an available list of provided programs. (2) The run-time system is an event-driven system for processing images. After a new image (or video frame) is acquired, a callback function is invoked. Currently, the data streams are treated independently; thus, this system is intrinsically parallel and can scale up to process thousands of data stream simultaneously. (3) The resource manager allocates the appropriate number of cloud instances to execute the analysis programs. The cloud instances are responsible for retrieving the visual data from the cameras and executing the analysis programs in real-time. The instances may include GPUs (graphics processing unit).

3.5 Resource Manager

Inside the computing platform, the resource manager is a crucial component of CAM² for automatically scaling the computational resources to meet analysis programs' demands. Some applications (such as transportation management and emergency response) need to analyze data only at certain time periods (rush hours or when a disaster occurs). Thus, the resource manager needs to adjust the allocated resources as the needs rise and fall. Many factors can affect the resource manager's decisions. Cloud vendors offer dozens of instance types with various amounts of available processor cores, memory, GPU cores, storage, etc. Furthermore, cloud instances of the same capability (same number of cores and same amount of memory) have up to 40% of difference in cost [7].

When the required computation and monetary costs are known for an analysis program, the optimal solution can be determined via a convex optimization problem [13]. It assumes computation and memory use scales linearly with the number of cloud instances; this is a reasonable assumption since this is the guarantee provided by the host of a cloud instance. The paper shows the optimal cloud instance is the minimum ratio between the cost of a given cloud instance and the provided computation power (in terms of memory and CPU speed).

To make the problem even more challenging, resource requirements depend on the content of the data as well as the analysis programs. A study suggests using multi-dimensional bin packing to model the relationships between the needs of analysis programs and the characteristics of cloud instances [7]. The method reduces overall cost by up to 60%.

However, when the geographical distance (hence, network round-trip time) increases, the data refresh rate may decline [14], [15]. The network camera's image quality can suffer. As a result, it is necessary to select a data center that is close to the network cameras if a high refresh rate is desired. This is an issue as network cameras are deployed worldwide and cloud data centers are located in many different parts of the world. Therefore the cost, location, and required image quality for analysis must be considered together for determining the proper cloud instance [16]. By modifying the original bin packing method [7], the new study shows a reduction in cost by 56% when compared with selecting the nearest location and further improved the original method by 36%.

4 OPPORTUNITIES AND CHALLENGES

To realize the applications outlined in Section 2, the following research opportunities and challenges must be investigated.

4.1 Automatically Adding Network Cameras

Adding network cameras to the CAM² database must be further automated to utilize the vast amount of network camera data still yet to be discovered. The challenges of using public network camera data leave this valuable data source largely unused. Network camera discovery is challenging due to the lack of common programming interfaces of the websites hosting network cameras. Different brands of network cameras have different programming interfaces. Different institutions organize the data in different ways. Such heterogeneity hinders the usability of the real-time data in emergencies. In other words, network camera data is not readily indexed. For example, there

is no easy way to generate images from all the live public network cameras in New York City. A web search will yield websites that point to camera data in New York City. But the data is spread across many websites, and it is not clear how to easily aggregate images from relevant cameras. To solve this problem, the CAM² team is (1) building a web-crawler to work with many different website interfaces and (2) building a database to provide a uniform interface via a RESTful API. The current version of the RESTful API has been released and the Purdue continues discovering network cameras.

4.2 Contextual Information as Weak Labels

The proper estimation of meta-data related to each network camera provides useful functionality in the future. Location and time of day provides useful information for automatic dataset augmentation. Information such as location and time can be called *contextual information* of the image/video data. As an example, a camera deployed on a busy highway is unlikely to see rhinos or buffaloes. If such an animal does appear on the highway, this unusual event is likely reported by news (also can be looked up by time and location). In contrast, a network camera watching a waterfall in a national park should not see semi-trucks. Time also provides contextual information about the visual data. The streets in New York City are usually filled by vehicles. On rare occasions (such as a parade shown in Figures 1 (e)-(g)), the streets are filled by people. Thus, this network cameras data can provide *almost correct* labels by simply assuming there exists vehicles in the data, modifying the label with cross-referenced news reports (of a parade) and other anomaly detection can form a type of *weak supervision* [17].

Weak supervision refers to using labels that can be (1) automatically generated using partially true rules (c.f. examples above), (2) utilizing related ground-truth labels that are not for exactly the same task, (3) boosting, (4) hand labeling with unreliable, non-expert annotators. Current research demonstrates how different types of weak supervision can be used to improve the accuracy of machine learning models [17]. Contextual information provides weak labels similar to (1), and we suspect future work will also improve model accuracy for image and video tasks, such as classification and object detection.

This contextual information can be easily derived if a GPS (Global Positioning System) receiver is included in every camera that is deployed outdoors. GPS receivers are already in every mobile phone and it is expected that all future network cameras will also be equipped with GPS receivers. Time and location may be referenced by sunlight and sun location. Location

can be even further refined by significant landmarks. For cameras deployed indoors, methods also exist for positioning them [18].

Other contextual information such as indoor/outdoor and urban/rural can be derived from a set of images using a variety of available computer vision methods. If needed, a new dataset of contextual information can be created. By training a computer vision method on the dataset, and contextual information can be automatically generated. While this is only an approximate solution, it is feasible that this will be sufficient for weak labels.

4.3 Network Camera Data is Distinct

As described in [8], commonly used datasets are distinct from each other. For example, the images used in ImageNet [2] can be distinguished from images used in COCO [3]. Furthermore for object detection tasks, labelled objects are more centrally concentrated for ImageNet than for COCO. This difference is a result of the different data distributions. Existing computer vision solutions tend to focus on developing accurate models for a small number of data distributions. Even when models are compared across many different datasets, the solutions' applicability beyond these datasets is unclear. The testing error of recently developed models can be overly optimistic even for samples from the same data distribution [19]. Since the visual data from network cameras may be considered *distinct* from other datasets, the simple re-purposing of a model's weights from a similar task may be insufficient. Instead, more sophisticated *transfer learning* methods may be required to mitigate the differences among datasets. Additional evidence would be needed to demonstrate that such techniques can handle the wide range of visual data from thousands of network cameras. Future work can investigate the degree to which models trained on available data can be transferred, and the best method for transferring the model's information. If needed, this may require an expansion of the existing CAM² dataset for each specific application [8].

4.4 Improving Models for Emergency Response

The data seen during emergency events is uncommon. Thus, the accuracy of machine learning models to respond to emergencies is likely poor. We propose three methods to improve machine learning in the event of an emergency. (1) Periodically record data before a disaster for an anomaly detection system. (2) Connect CAM² to a infrastructure for crowd-sourcing to gather labelled data on short notice from locations known to have an impending emergency situation. For

example, crowd-source was used in the Haiti earthquake of 2010 [20]. It is conceivable to create a similar infrastructure for images and video in an emergency. (3) Network cameras need to have a uniform interface for easy access in emergency situations, given the proper privacy and legal constraints [21].

4.5 Dataset Distinctiveness for Active Learning

Finding the right subset of data to label is a general question in machine learning, especially during an emergency when time is short. The problem is also applicable to non-emergency scenarios when the cost of labelling data is the constraint, rather than time.

As network camera data is distinct, we wish to further investigate if dataset distinctiveness can be used to improve active learning methods. In this paper, active learning is defined as following: Given a large number of unlabeled data, we must identify the right subset of data to label. A general framework for active learning methods is often given as the balance between measures of (1) how “representative” (or typical) the sample of data is relative to the true data distribution and (2) maximizing variance reduction of the model (equivalently, minimizing the true risk). Often, the product of the two measures is used to identify the best samples. With an input-output pair, this can be thought of as (1) modeling only the data and (2) modeling only the conditional distribution. Multiplying them together can be thought of as modeling the unnormalized posterior. Since network camera data is distinct from the existing datasets, the use of this new data source may improve the current active learning methods.

4.6 Adaptive and Programmable Network Cameras

Another improvement is to make network cameras “self aware” of the context being seen, so as to automatically execute relevant programs. It may be possible for stationary cameras to determine the visual information being captured and install/execute computer vision programs specialized for the content. Moreover, network cameras may need to be reprogrammed in emergencies. The street cameras in Figures 1 (e)-(g) may be specialized for detecting congestion and accidents in normal conditions. During a parade, the cameras may need to be reprogrammed to search for a lost child [22].

5 CONCLUSION

Network cameras provide rich information about the world. The visual data has many applications, including real-time emergency response and discovery

of long-term trends. This paper presents a software infrastructure called CAM² (Continuous Analysis of Many Cameras) constructed at Purdue University for acquiring and analyzing data from network cameras. The paper suggests many opportunities using the data and challenges to be conquered.

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