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Real Time Automated Machinery Threat Detection and Identification System for Pipeline Infrastructure Protection

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Abstract

Consistent monitoring of a right-of-way (ROW) is an important task for protecting the integrity of pipeline infrastructure. Pipeline monitoring is typically conducted visually by ground based and airborne inspection crews. In this paper, we present a real-time full-fledged automated airborne monitoring system that can detect, recognize, and localize machinery threats such as construction equipment, occurring on a pipeline ROW. In our approach, a modular key frame (MKF) selection technique is developed to improve data processing speed, a pyramid Fourier histogram feature is used for feature extraction, and a cascaded classifier is introduced for object categorization. Experimental results using two real-world datasets indicate that the proposed system is able to detect and recognize objects in challenging environments such as low illumination, varying resolution and partial occlusion. The results also show that our system can reach real-time processing speeds with good accuracy which offers a new and useful tool for wide area pipeline surveillance.

Introduction

The most common threat to a pipeline ROW is unauthorized construction equipment capable of digging into a ROW potentially damaging the pipeline and causing a leak, U.S. DOT [1]. Pipeline incidents caused by excavation damage can result in fatalities and injuries, as well as significant cost, property damage, environmental damage, and unintentional fire or explosion. Pipelines typically span long distances over varying terrain making pipeline surveillance a difficult, expensive, and time consuming task. Aircraft are commonly used to inspect pipelines and airborne imagery is often collected to document the threats along the ROW. Analysis of the extensive quantity of aerial imagery collected during a surveillance mission is a challenging, time consuming and computationally expensive task for human analysts. Therefore, we developed a fully automated image processing system that can perform real-time machinery detection and identification tasks to improve pipeline inspection, reduce analysis effort, and enhance the safety of pipeline infrastructure.

Analyzing aerial surveillance videos containing thousands of frames manually is a difficult task for human analysts. Even for a computer vision based algorithm, the examination every frame in a surveillance video is not a meaningful process when some of the frames do not contain significant information. It would be much more efficient to only examine the frames that contain important information. If frames containing important information can be selected and processed, then the entire computation time can be reduced significantly. To this end, we improved upon our previously developed modular key frame (MKF) selection strategy [2] to achieve better accuracy and to reach real-time performance.

Vehicle detection has been an interesting focus for machine vision applications. Zhao et al. [3] utilized the features from the edges of the front windshield and shadows to detect cars, while a four elongated edge operator was used for vehicle identification in [4]. Grabner et al. [5] introduced an on-line boosting method based on implicit appearance models for car detection, whereas in [6], a set of feature extraction and classification methods were exploited for vehicle detection from aerial imagery. Recently, a hybrid deep convolution neural network approach was developed for vehicle detection in satellite images [7]. In our earlier work [8, 9, 10], we designed a multistage framework, which utilizes monogenic features and a part-based model for automatic machinery threat detection on a pipeline ROW from aerial imagery. In this work, a hardware-software integrated automated system was developed. The algorithm flow can be seen in Fig. 1.

The scheme consists of six stages: 1) database connection and loading, 2) key frame selection and key region selection, 3) feature extraction, 4) object detection, 5) object identification, and 6) threat priority assessment. In the first stage, a PostgreSQL database server, controller, and executable software are connected, such that the incoming frame is loaded and processed in real-time. The second stage performs the key frame extraction by selecting the frames that contain salient information and discarding the rest from further actions. Then a key region selection technique is used on the selected key frames. Following key region selection, a pyramidal Fourier histogram of oriented gradients [11] feature is employed for feature extraction in each key region. As for object detection and identification, a support vector machine [12] with radial basis kernel is used, and a cascaded multiclass object recognition approach is applied for object identification. Lastly, the threat priority is automatically assigned for each detected object. Meanwhile, a Keyhole Markup Language (KML) file is generated for expressing geographic annotation and visualization within mapping software such as Google Earth and various Geographic Information Systems (GIS). In this paper, we focus on the scheme stages from 2 to 6.

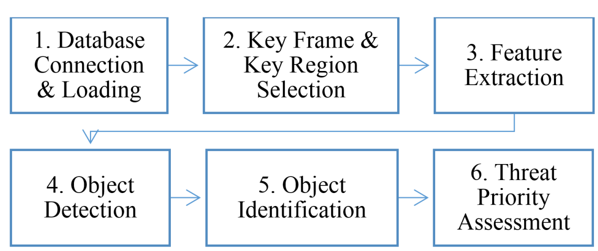

Figure 1. *Block diagram of the proposed scheme.*

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Technical Approach

Key Frame Selection

The aim of MKF selection is to best represent the prominent contents contained within a video with the minimal number of frames. In real-world implementations, such airborne pipeline monitoring, key frame selection methods must be capable of performing in real-time. Thus, we developed a new MKF technique, which is based on cumulative batch updating and sub-region dividing, with speeds suitable for real-time processing.

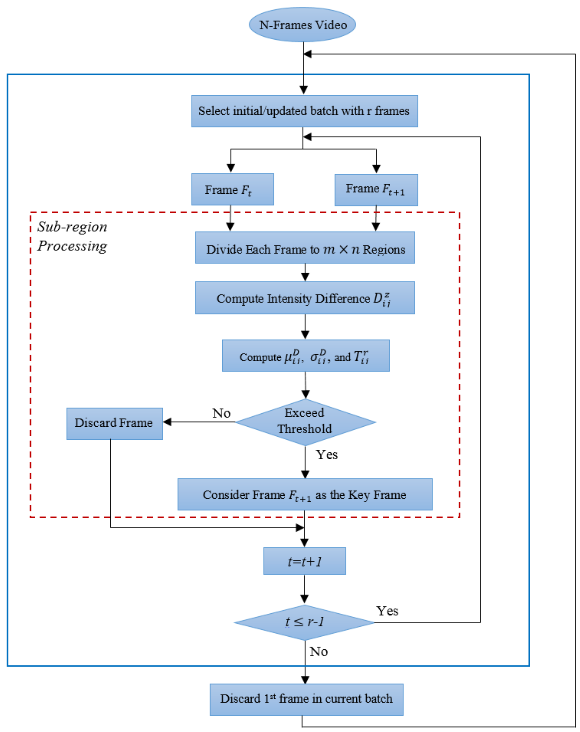

Figure 2. *Flowchart of the proposed MKF technique. F_k represents the current frame.*

In this algorithm, a set of frames is required to create an initial batch with r number of frames, and each frame is partitioned into $m \times n$ sub-regions in a batch. Then the intensity differences between the corresponding sub-regions in two consecutive frames are calculated. Following that, we compute global means and standard deviations for each sub-region are calculated. During this process, an adaptive threshold is obtained using the global mean μ^g_{ij} with its corresponding standard deviation σ^g_{ij} in the $(ij)^{th}$ sub-region, expressed as

$$T_{ij} = \mu^g_{ij} + \sigma^g_{ij} = \frac{1}{r-1}\sum_{z=1}^{r-1} D^z_{ij} + \sqrt{\frac{1}{r-1}\sum_{z=1}^{r-1}\left(D^z_{ij} - \frac{1}{r-1}\sum_{z=1}^{r-1} D^z_{ij}\right)^2} \quad (1)$$

where T_{ij} represents the adaptive threshold of all $(ij)^{th}$ sub-regions, r is the number of frames in the initial batch, and D^z_{ij} represents the $z^{th}(z = 1, 2, , r-1)$ pixel-wise intensity difference between $(ij)^{th}$ ub-regions in two consecutive frames. Using T_{ij}, a key frame can be determined by

$$\begin{cases} D^z_{ij} > T_{ij} \; for \; any \; (ij) & : \; key \; frame \\ D^z_{ij} \leq T_{ij} \; for \; any \; (ij) & : \; not \; a \; key \; frame \end{cases} \quad (2)$$

Once the key frames are extracted from the initial batch, we add a new frame (frame next to the last frame of the batch) to this batch and discard the first frame in the initial batch, then we determine whether the new frame is a key frame or not. This step is repeated until processing all frames in the datasets. A flowchart of the described MKF technique is presented in Fig. 2.

Key Region Selection

Based on our observations of real world data, the occurrence of objects of interest (i.e., construction equipment) in a scene is random with varying sizes, colors, textures, and orientations. However, objects of interest (targets) present stronger corners compared to the background [11]. Thus, we extract potential regions-of-interest (ROI) that may contain target objects with the help of the Harris corner detector [13]. It is worth noting, that there could be more than one corner on a single object (see Fig. 3(c)). Multiple corners occur because of the complexity of a targets structure. This can result in the detection of the same object several times in one location. Our approach to handling this issue is to fuse two or more corners based on predefined distance among the corners and select the strongest twenty corners from the key frames. In the case of any two key regions having 25% or more overlapping areas, we discard one of them to avoid the repetition. Fig. 3 illustrates the key region selection procedure, where Fig. 3(a) shows the original image, the results of the detected corners are shown in Fig. 3(b). Fig. 3(c) demonstrates the twenty strongest corners, and the final predicted key regions are presented in Fig. 3(d) where it is obvious that a target object (i.e., excavator) is within the selected key regions.

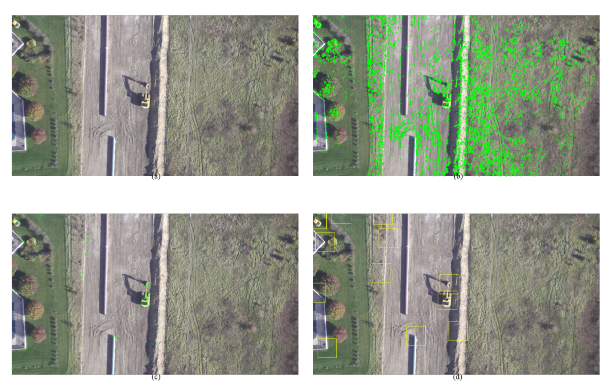

Figure 3. *Key region selection illustration, (a) input image, (b) initial detected corners, (c) the selected first 20 strongest corners, and (d) the final estimated key regions.*

Pyramidal Approach for Feature Extraction

Once the key regions are obtained, we extract robust features from the regions to achieve better target classification perfor-

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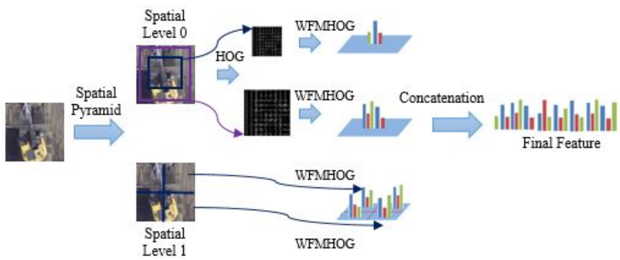

Figure 4. *Illustration of WFPHOG. WFMHOG: weighted Fourier magnitude HOG.*

mance. We extract features using a pyramid histogram of oriented gradients (PHOG) [14, 15, 16] in the Fourier domain (only magnitude is considered) with corresponding weighting. This technique is named Weighted Fourier PHOG (WFPHOG) [[11]. Fig. 4 illustrates the concept of the WFPHOG approach, where there are three main processes. In the first, (level-0), we divide each sub-region into two square regions with linearly increasing areas, then compute HOG feature and map it to a discrete Fourier domain with associated weighting. In the second, (level-1), we partition the key region into four sub-regions and then WFPHOG is computed for each individual region. The final feature is built by concatenating the features from all levels of the pyramid regions.

Object Detection and identification

After the feature extraction stage, we incorporate a cascaded object classification algorithm to determine the presence of the objects. Five steps are performed in this stage. First, we apply we apply the Radial basis function (RBF) based support vector machine (SVM) classifier through all extracted features from the estimated key regions and obtain a confidence score for each target object. Second, all false detections and true detections collected and used to produce a new set of training data. Third, we train a new classifier using the new training sets. Then fourth, we apply the RBF-based SVM classifier algorithm again to produce another confidence score. Last, we combine current and previous classification scores and compare it with a threshold. If the combined score is higher than the threshold, the system will define the key region that contains a target threat, or if the combined score is lower than the threshold, the system will define the region as having no threat target. The above five steps may repeat if there is a false detection found after the step 5. This process will continue until there is no false positives detected. Fig. 5 depicts the object detection and identification process.

In object identification, the algorithm will receive the true signals (the detected objects) from the object detection model, then the extracted WPFHOG feature is fed to a SVM based multi-class classifier to perform the recognition task. For object recognition, we manually selected over five hundred images, which are from the detected objects in the previous dataset, as training samples and categorized them into 6 classes (5 object classes and 1 unknown class). Due to the current limitations of the training data, we currently identify only 5 object categories. The capability of the system will increase as more airborne image data is collected and as more new objects of interest are identified and classified.

Threat Assessment

It is critical that the operator be able to quickly dispatch personnel to the location of an unauthorized intrusion of machinery into the ROW. Therefore, it is necessary to know the geolocation of the threat object. To meet this need, we designed a framework that can automatically produce coordinates of the detected threat objects. The targets coordinate information is stored in a KML file which can be easily loaded in mapping software such as Google Earth/Map, ArcMap, or other GIS software to geographically locate and visualize the detected machinery threat targets. In addition, our system automatically assigns a priority level to any given threat as high, medium and low depending on the targets distance from the pipeline. More details of the distance computation can be found in [9].

Experiments and Discussion

To demonstrate the performance of our proposed method, two real-life datasets were used. These two datasets were captured by a traditional pipeline surveillance aircraft flown at altitudes of 1000 to 1300 feet AGL. The video image resolution was 1920×1080 pixels, and the two datasets contained 4380 and 10983 frames respectively.

To train our system, we manually selected the positive video frames (the images with construction vehicles) and negative video frames (the images without construction vehicles) from the captured datasets. As for parameters in feature extraction, we set an 18-bin histogram for WPFHOG with two levels of spatial pyramid (see Fig. 4). This constructs a feature vector length of $108(18+18+4\times 18)$ pixels. Once the final feature is obtained, a support vector machine with Radial basis kernel is used as the classifier to detect and identify objects.

For evaluation, we manually defined the ground truth from the testing datasets, and the different evaluation metrics are computed as follows:

- True Positive Rate (TPR): the proportion of actual positives that were correctly classified as positive threat objects (vehicles) in the detected target images.
- False Positive Rate (FPR): the proportion of actual negatives that were incorrectly classified as positive threat objects in the total number of detections.
- False Negative Rate (FNR): the proportion of missed detected threat objects in the detected target images.

Table 1 summarizes quantitative results on the object detection for both datasets, and some sample detection results on the images are shown in Fig. 6. As it can be seen, our approach

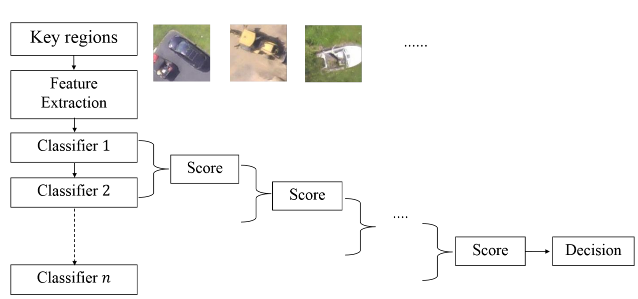

Figure 5. *Concept of the proposed object detection process.*

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achieved a 93.6% to 95.4% TPR with a 17.7% to 22.9% FNR for both datasets. TPR and FNR are likely to improve with the addition of new training data. While outputting the detection results, our system is also able to identify object types and automatically issue warnings regarding the severity of the detected objects by providing useful information such as object geolocations, threat priority, as well as the KML files for mapping and documenting the detected objects with mapping systems such as Google Earth/Map, ArcMap, or other GIS software.

Table 1: Quantitative evaluation of the detection performance

Dataset	Number of Frames	TPR	FPR	FNR
Dataset 1	4380	93.6%	22.9%	6.4%
Dataset 2	10983	95.4%	17.7%	4.6%

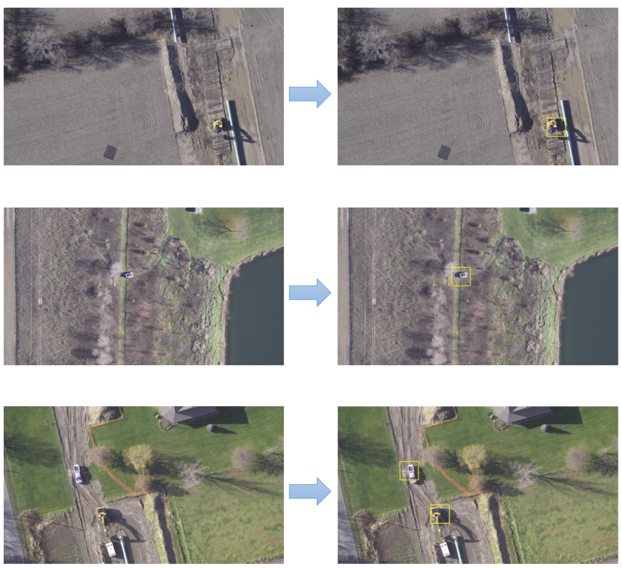

Figure 6. *Sample results. Left are the input images and right are the output images with detected objects marked as yellow bounding box.*

Conclusion

In this paper, we introduced an automated airborne pipeline monitoring system that can be used to monitor pipeline ROWs for unauthorized intrusions of construction equipment. Our framework includes several distinct stages to detect and identify machinery threats to the pipeline ROW, and to issue warnings regarding the severity of the detected objects. We simulated and tested this proposed technique under challenging conditions to investigate its capability and reliability. Test results show that our system can achieve real-time performance with good accuracy. Based on these results, we are confident that our automated airborne pipeline monitoring system can be used as an accurate, efficient, and practical tool for wide-area pipeline ROW surveillance.

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References

[1] U.S. Department of Transportation Pipeline and Hazardous Materials Safety Administration, A Study on the Impact of Excavation Damage on Pipeline Safety Report to Congress, (2014).

[2] Almabrok Essa, Paheding Sidike, and Vijayan K. Asari, A moudular approach for key-frame selection in wide area survillance video analysis, Proc. IEEE National Aerospace & Electronics Conference & Ohio Innovation Summit, pg. 1-4. (2015).

[3] Tao Zhao and Ram Nevatia, Car detection in low resolution aerial image, Proc. Eighth IEEE International Conference on Computer Vision (ICCV), pg. 710-717.(2001).

[4] Hankyu Moon, Rama Chellappa, and Azriel Rosenfeld, Performance analysis of a simple vehicle detection algorithm, Image and Vision Computing, 20, 1-13(2002).

[5] Helmut Grabner, Thuy Thi Nguyen, Barbara Gruber, and Horst Bischof, On-line boosting-based car detection from aerial images, ISPRS Journal of Photogrammetry and Remote Sensing, 63, 382-396(2008).

[6] Joshua Gleason, Ara V. Nefian, Xavier Bouyssounousse, Terry Fong, and George Bebis, Vehicle detection from aerial imagery, Proc.IEEE International Conference on Robotics and Automation (ICRA), pg.2065-2070. (2011).

[7] Xueyun Chen, Shiming Xiang, Cheng-Lin Liu, and Chun-Hong Pan, Vehicle Detection in Satellite Images by Hybrid Deep Convolutional Neural Networks, IEEE Geoscience and Remote Sensing Letters, 11, 1797-1801(2014).

[8] Binu Nair, Varun Santhaseelan, Chen Cui and Vijayan K. Asari, Intrusion detection on oil pipeline right of way using monogenic signal representation, Proc. SPIE Signal Processing, Sensor Fusion, and Target Recognition XXII, pg. 87451U.(2013).

[9] Vijayan K. Asari, Paheding Sidike, Chen Cui, Varun Santhaseelan, Recent progress in wide-area surveillance: protecting our pipeline infrastructure, Proc. SPIE Imaging and Multimedia Analytics in a Web and Mobile World, pg. 940802.(2015).

[10] Vijayan K. Asari, Paheding Sidike, Chen Cui, and Varun Santhaseelan, New wide-area surveillance techniques for protection of pipeline infrastructure, SPIE Newsroom: Defense and Security, 1-4(2015).

[11] Paheding Sidike, Almabrok Essa and Vijayan K. Asari, Intrusion detection in aerial imagery for protecting pipeline infrastructure, Proc. IEEE National Aerospace & Electronics Conference & Ohio Innovation Summit, pg. 1-3.(2015).

[12] Corinna Cortes and Vladimir Vapnik, Support-Vector Networks, Machine Learning, 20, 273-297(1995).

[13] Chris Harris and Mike Stephens, A combined corner and edge detector, Proc. of the 4th Alvey Vision Conference, pg. 147-151.(1988).

[14] Navneet Dalal and Bill Triggs, Histograms of oriented gradients for human detection, Proc. IEEE Computer Society Conference on Computer Vision and Pattern Recognition, pg.886-893.(2005).

[15] Svetlana Lazebnik, Cordelia Schmid, and Jean Ponce, Beyond Bags of Features: Spatial Pyramid Matching for Recognizing Natural Scene Categories, Proc. IEEE Computer Society Conference on Computer Vision and Pattern Recognition, pg. 2169-2178.(2006).

[16] Anna Bosch, Andrew Zisserman, and Xavier Munoz, Representing shape with a spatial pyramid kernel, Proc. of the 6th ACM interna-

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tional conference on Image and video retrieval, pg. 401-408.(2007).

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