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Conference Paper · November 2015

DOI: 10.1109/DICTA.2015.7371267

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Image Analysis-based Automatic Utility Pole Detection for Remote Surveillance

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***Abstract*—In case of disasters such as cyclones, earthquakes, severe floods etc., widespread damages to infrastructures such as power grid, communication infrastructure etc. is commonplace. Especially to power grid, the damages to various structures are typically spread out in wide areas. Usage of drones to do fast remote survey of damage area is gaining popularity. From the remote surveillance video of any wide disaster area that is fairly long, it is important to extract keyframes that contain specific component structures of the power grid. The keyframes can then be analyzed for possible damage to the specific structure. In this context, we present an algorithm for automated detection of utility poles. Specifically, we show robust detection of poles in frames of videos available from various sources. The detection is performed by first extracting 2D shapes of poles as analytically defined geometric shape, quadrilateral, whose edges exhibit noise corruption. A pole is then detected as a shape-based template, where one long rectangular trapezium, is perpendicularly intersected by at least one trapezium representing a crossarm that suspends the conductors. Via testing and comparison, our algorithm is shown to be more robust as compared to other approaches, especially against highly variable background. We believe such detection, with limited false negatives, will form stepping stone towards future detection of damages in utility poles.**

***Index Terms*—Object Segmentation, Utility Pole Detection, Image Analysis, Remote Surveillance**

I. INTRODUCTION

In any nation, maintenance of critical utility service is an important and costly legal responsibility, mainly for public safety, of any distribution/service provider company. Infrastructures for such services include power grid, oil/gas pipelines, railway corridor etc. These outdoor systems are **vast** in the sense that their installation area runs into tens of kilometers. Faults and damages can occur due to disasters, ageing of components, severe weather, overloading, overstraining etc.

Especially during disasters and emergencies, structural damage to conductors, poles, towers etc. are commonplace, other than excess sagging of conductors, short-circuiting etc. In past, we have carried out research on image-based analysis of many of these components in damage scenario, and published our results[1], [2], [3]. However, from experience shared by power grid corporations in various countries, given comparably smaller cross-section area that bears high weight, utility poles get damaged/bent more often than other components. The distribution company then strives to repair the damaged grid in earliest time-frame in order to restore the critical supply. In the aftermath of disasters, the damage to utility poles is spread out in vast area, at undetermined locations. To be able to efficiently deploy technical staff to go in field and do restoration work, so as to minimize restoration time, it is quite important to be able to locate the possible locations at which damages have happened. An emerging popular option for shortlisting is to employ a commercial Unmanned Aerial Vehicles (UAV) to do a fast mission over vast damage area, and collect the aerial surveillance video. The surveillance video can then be analyzed first for locations at which specific object of interest are located, and then for damage detection and characterization of degree of damage. The video generated out of survey of a vast area tends to be quite long. Hence, towards the goal of first stage of analysis, it is needed that an automated, fast algorithm efficiently extract **keyframes** from the video in which specified object (utility pole in our case) is detected. Any subsequent analysis of this much smaller (sub)set of frames to assess the degree of damage to poles at various locations is used to do efficient scheduling and deployment of technical staff during restoration efforts [4].

Automated detection of utility poles from rural/urban background is *challenging* for several reasons. One reason is that more than one type of poles exist, having different shapes, appearance features and physical dimensions. Also, occlusion can happen due to *shadow* of some other object nearby, falling on the pole. Part of the pole, especially its bottom can be occluded by low-height shrubs. Occlusion due to posters, painting of label etc. has also been commonly observed by us. Finally, as a common problem for most long linear objects [2], foreground area is very small and homogeneous when compared to vast, heterogeneous background, and there can be many false positives for such objects.

For our problem, only a handful of research works exist in literature. [5] provides a way for using laser scanning data for 3D modeling of poles etc. However, mounting and using laser scanner on a UAV is not commercially viable in general. Similar problem is expected to arise if the approach suggested in [6] is followed. Also, their usage of projected height as a feature in the classifier design is not robust: dependent on camera pose etc. In [7], machine learning approach is used in eventual 3D modeling, both of which are time-consuming and unsuitable for being used towards quicker decision-making requirement in disaster scenarios. The aim of work in [8]

Fig. 1: Block diagram of Utility Pole Detection Algorithm

is to extract street light pole, for which they consider joint detection along with a lighting fixture. Such detection is very restrictive since it omits detection of power grid segments that are employed purely for power distribution, unlike our work. Also, they detect only vertical poles, while our algorithm can detect leaning or bent poles as well, as is the case most often in disaster scenarios. The method proposed in [9] uses Radon transform. We experimentally found that their algorithm works well *only* for partial pole images, and on *sky as homogeneous background*. Similarly, the method adopted in [10] is to detect pole shadow in an image, and locating the pole base. This approach is severely restrictive since the shadow need not fall on a flat terrain/plane, and hence may be piecewise-rectangular. In [11], the pole is detected by locating the corners of the pole-top in aerial imagery. However, since the pole-top is typically rough, not only many false corner features are detected, but also in case of leaning poles, the true corners of pole top may get mingled in random-textured ground as background, since pole is now closer to the ground than to the aerial camera platform. To summarize, for design of computationally light algorithm, we take a **shape-based approach** for pole detection, *not* been taken by any prior work known to us.

In this paper, we consider a *reinforced concrete-based pole* (c.f. Fig. 2a,3a), which is most commonly used throughout India, as part of power distribution grids upto 66 KVolts. This is due to high breaking stress known for this material, which enhances its durability. We propose a five-stage detection algorithm, which has following properties.

- Shape as a feature will remain unchanged even in a damage scenario, since the material used for poles is reinforced concrete, which has v. The pole can break or bend, but cannot take form of another shape.
- While 3D shape modeling and detection via partial/full matching would be more accurate and robust, to our understanding, most of the popular 3D shape descriptors and corresponding dissimilarity-based matching functions are computationally heavy [12], [13]. For the requirement of faster detection, we devise a new algorithm that works by 2D shape detection.
- Even in 2D scenario, we devise a computationally light shape detection technique by considering analytical/parametric shape in form of trapezium, that works along contour of shapes whose linear edges have been corrupted by noise. Hence we do not follow the standard method of employing Hough/Radon transform for extracting parametric shapes [14], which has known higher complexity.
- Occlusion being a big challenge, we have simplified [15] and designed a *novel* light-weight block-based shape extraction and region merging technique, to extract pole-like structures. Usage of this technique brings down the quite an amount of false negatives.
- Our method can robustly detect a pole with any degree of leaning, not just vertical poles.
- We use context information of having at least one cross-bar, necessarily present in a live grid to suspend insulators supporting the conductors mounted on its either side, perpendicularly intersecting the pole-like structure, to weed out false positives.

The rest of the paper is organized as follows. We first discuss the intuition behind our approach in section II, before describing our detection algorithm in section III. We then describe data collection approach in section IV, followed by the section V on results and analysis. We briefly discuss implementation of a smartphone app using our algorithm, in section VI, before concluding the paper in section VII.

II. Approach to Object Detection

Against vast outdoor background especially in case of aerial imagery, one challenge is that the foreground object of interest has no special color or texture feature, that can be used for basic appearance-based pole segmentation. The most important feature is thus its **shape**: each face of the pole is a trapezium, a regular shape, due to standard design. In fact, each face is a long trapezium, since poles are tall structures. However, occlusion typically introduces discontinuities in the detection of any such face. This leads to detection of closely-located parts per face. Hence, rather than using any holism-based global descriptor for shape [16], we follow the alternative philosophy of structuralism in shape, and compose the shape of each face from its parts that are detected in one-another's vicinity. To be able to isolate detection of utility pole against false positives in outdoor scene e.g. dead tree stump, we have to employ context-based recognition at last stage.

The construction standard of utility poles is such that the two dimensions in its horizontal cross section are not equal: one is *almost half* of the other. Since from any pose, for any cuboid shape, at most two faces can be visible, we proceed by establishing the trapezium shape of closest and widest face of the pole, further bolstered by context-based recognition.

A machine learning approach to design a classifier for this object is the best approach possible for robust design. However, for our application, no public dataset exists, to the best of authors' knowledge. Also, to collect and have our own large **aerial** image dataset has been impractical for us so far. Hence we follow the routine detection approach via feature-based segmentation and detection of object of interest.

III. Proposed Algorithm

The algorithm consists of five stages, as in Figure 1 and described in Algorithm 1. Their description is as follows.

A. Preprocessing: Mean-shift Segmentation

Given complex outdoor, typically urban background of a pole, various edge detection algorithms significant number of edges in the background as well. Simultaneously, one of utility pole's prominent feature is the presence of edges. To distinguish pole's edges, we need to reduce background clutter and simultaneously accentuate the foreground. For this, we first filter the images. The mean shift based image segmentation is a straightforward extension of the discontinuity preserving smoothing algorithm. A comparison of various segmentation algorithms using objective evaluation measure is described in [17]. The authors found that foreground clustering arising from mean shift outperforms other popular segmentation schemes, for outdoor images [1], [3]. We use the optimized mean shift scheme proposed in [18]. The *typical* output of such segmentation for Figs. 2a,3a is shown in Figs. 2b,3b.

Algorithm 1 Detection of Utility Poles

Optimized mean shift-based filtering for suppressing background.
Blob extraction via color-based mean-shift clustering.
Quadrilateral shape determination using noisy edges of each blob.
Select all quadrilaterals which have at least one pair of almost-parallel edges, as candidate trapeziums
  For Each Trapezium
    Iteratively find a series of neighboring trapeziums who have similar orientation as the average of its parallel edges
    Extrapolate and merge such orientation-similar trapeziums into a longer trapezium
  EndFor
Detection of foreground cluster as Utility Pole based on context knowledge of intersecting crossarm.

B. Block-oriented Quadrilateral Extraction

Due to perspective projection, the long rectangular faces appear as trapezium in a 2D image. Further, the faces of any concrete structure e.g. pole are prone to wear and tear in form of *dents* due to shear. Hence there is "noise" in the edges of such imaged trapezium. Also, there can be occlusion along the length of the trapezium due to many reasons mentioned earlier. Hence the edge features are not continuous, but show variations in few segments. Finally, since the surface of the pole is *homogeneous*, any part of its face in shadow region, and any contiguous background that is also in shadow, has similar color properties.

Hence the intuition we follow is to try detect a "noisy" shape having similarity to a long trapezium. To do this, we first detect all possible quadrilaterals. This is done by first doing color-based clustering over the filtered image, to extract "homogeneous" blobs. We then ascertain the shape of each blob, and shortlist those which have a quadrilateral-resembling contour. The shape determination part has a 15% tolerance for noise in the edges. It is expected that few occluded parts of the pole do not appear as part of quadrilateral that bounds the pole, thus breaking up pole surface into multiple quadrilaterals. Further, in some parts, especially in shadow region, object contour can leak into background during floodfilling in an unstructured fashion, due to locally weak edges. Hence, again, these parts cannot be fitted into a quadrilateral easily. To *localize* these breakages in the pole quadrilateral, we divide each quadrilateral, whose bounding box is more than 25% of image height, into smaller ones whose bounding box is of size 10% of image height or less. In such case, as in Figs. 2c,3c, we detect a series of quadrilaterals, with few in the series missing due to occlusion or contour leak. The localization helps in reducing *false negatives*: we *extrapolate* around the localized breakages in the shape, as in next stage, thus being able to detect a pole in most of the real cases where occlusion and contour leak effects are commonplace. If the set of blobs after clustering are arranged in an arbitrary sequence b_i, then the subset of blobs that are quadrilaterals is defined as follows.

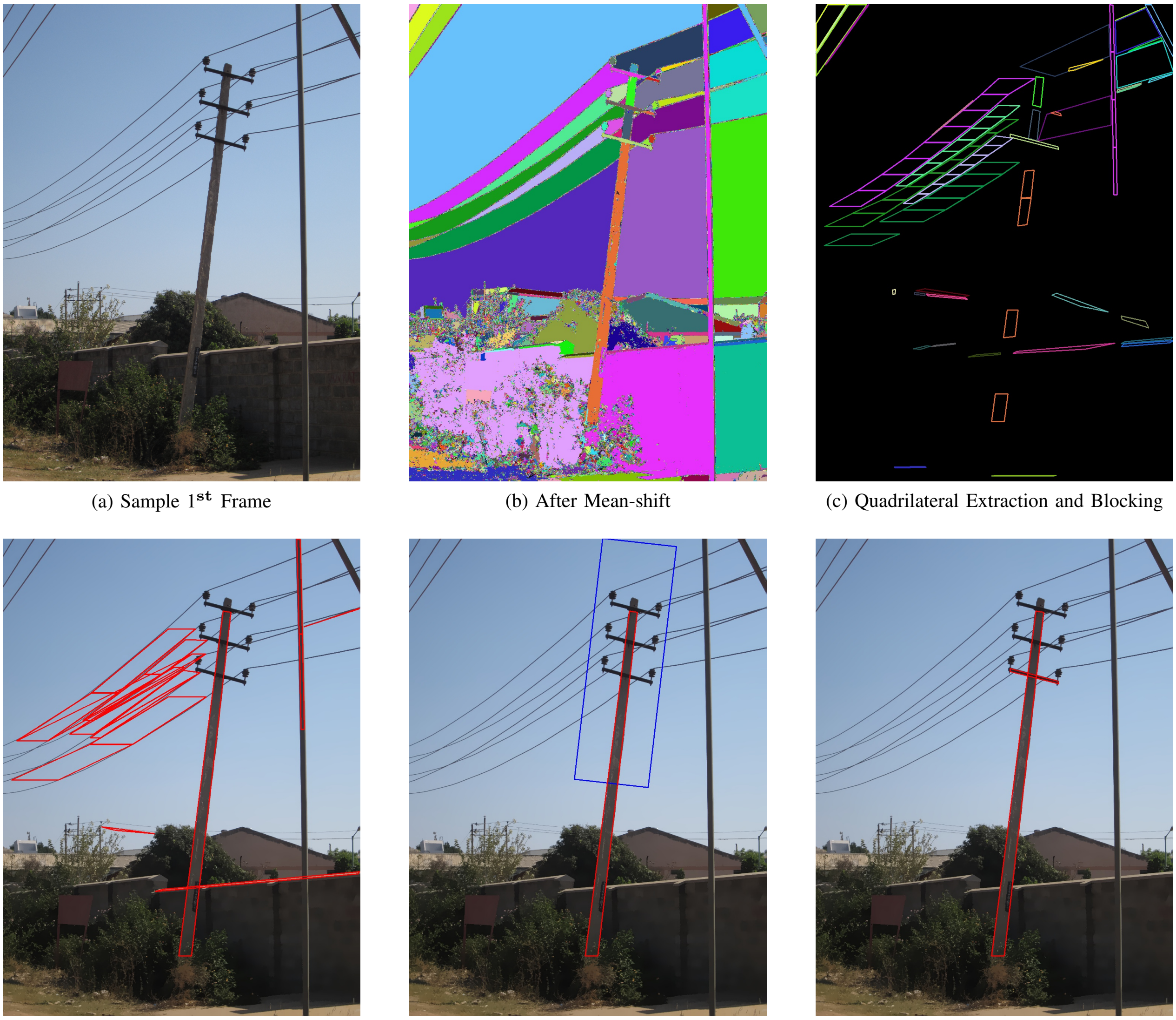
$$\{Quads\} = \{\exists b_i \in Blobs : No(Edge\{b_i\}) = 4\} \quad (1)$$

We could have used active contour methods for segmentation in wake of contour leaks, to account for weak edges, but it is well-known that most of the popular active contour methods have high computational complexity [19].

C. Orientation-based Spatial Clustering of Near-Trapeziums

After the last stage, the bounding trapezium of a pole corresponds to series of smaller detected trapeziums inside. While most of these trapeziums are contiguous, at few places, there are regions within the bounding trapezium which correspond to breakages/discontinuity, as mentioned before. Since the faces of a pole are homogeneous, especially in shape, we can fill up these *gaps* in shape by extrapolation using *region growing*.

To merge the detected trapeziums within a pole, we consider *orientation* as the underlying feature. Since a trapezium has at least two parallel edges, we represent the orientation of a detected trapezium by the average orientation of two *near-parallel* edges of a detected quadrilateral. We consider approximate parallelism, to factor in the noise in edges. We then cluster all quadrilaterals, which are of trapezium shape (at least one pair of edges are near-parallel), which have similar orientation, and the centroid of their bounding boxes are in the vicinity of a single hypothetical line connecting the centroids of the bounding boxes in image plane, having such orientation. To extrapolate for localized discontinuity in shape around this hypothetical line, we expect that the "gap" length, between centroids of bounding box of two successive quadrilaterals in a *merged segment*, be not more than 10% of image height. Assuming $Traps$ to be the subset of quadrilaterals that are trapeziums, t_i, t_j to be two arbitrary trapeziums in this subset, $angle\{t_i\}$ to be the orientation of the medial line of the



(a) Sample 1st Frame (b) After Mean-shift (c) Quadrilateral Extraction and Blocking

(d) Orientation-based Merging (e) Search Space for Crossarm (f) Final Detection

Fig. 2: Example Detection for First Pole

trapezium t_i, and $medial\{t_i\}$ be the physical location in 2-D pixel space of the medial line of t_i, the core model of construction a long trapezium out of various t_i's, depicting the utility pole, is as follows.

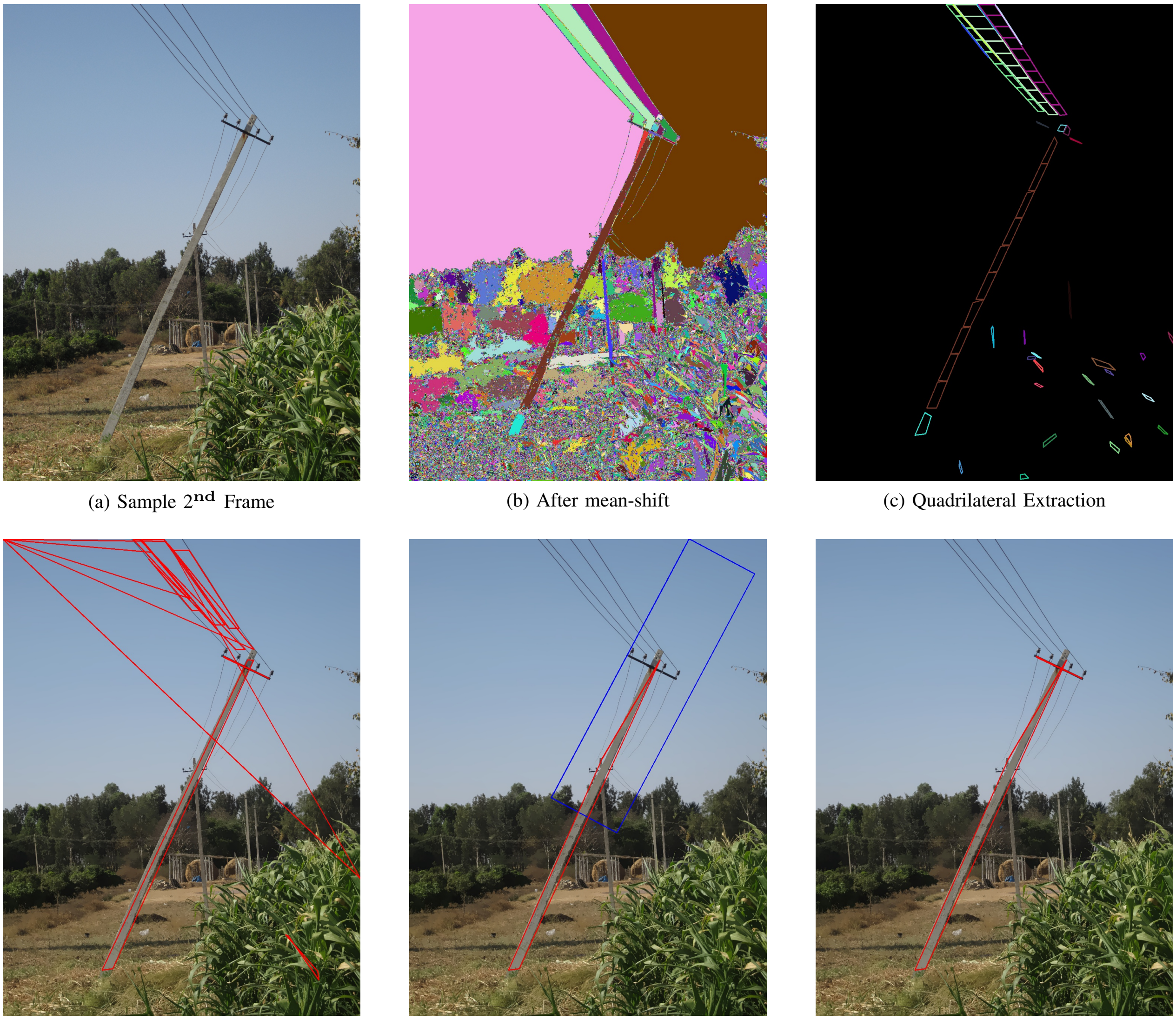
$$\{Long\ Trap.\} = \cup\{t_i, t_j \in Traps : \{angle\{t_i\} \approx angle\{t_j\}\} \wedge \{medial\{t_i\} \approx medial\{t_j\}\}\} \tag{2}$$

A typical output of this stage, based on block-level quadrilaterals as input from previous stage as in Figs. 2c,3c, is shown in Figs. 2d,3d. It can be noted that after this stage, in most images, along with many other long trapeziums as false positives, we are able to detect a major portion of utility pole as well.

D. Context-based Detection of Utility Pole

The output of previous stage results in highlighting of a set of trapeziums, which are long enough. A lot many of these trapeziums are false positives. To locate the true positive, we additionally use context information. Being part of a power distribution grid, one can always expect that the *top* of pole has at least one insulator, at least one conductor and at least one crossarm mounting at least one insulator that suspends the conductor, in its spatial vicinity. Moreover, all the crossarms are riveted to the pole in a *perpendicular* fashion, so that the gravitational load of symmetrically placed conductors gets balanced on the pole. Since crossarm is the relatively bigger structure among these, and also relatively prominent object in pole-top vicinity, we use presence of *at least* one perpendicularly placed crossarm, to one of the long trapeziums, as the additional context information. This in turn entails locating a long enough trapezium, and a short enough trapezium, the first of which represents part of a pole, and second represents part of a crossarm which may be detected only on one (left/right) side of the detected part of pole.

To be able to locate crossarms, *as many* of them, we follow similar approach that of detecting shapes and merging



(a) Sample 2$^{\text{nd}}$ Frame

(b) After mean-shift

(c) Quadrilateral Extraction

(d) Trapezium Merging

(e) Crossarm Search

(f) Final Detection

Fig. 3: Example Detection for Second Pole

the shapes in a way so as to extrapolate for locally missed detection. However, crossarms being thin structures, and also due to the presence of rivets, riveting plate etc. along the bar, the imaged surface of the crossarm is not just thin and small, but also has many corner points, some of which are located in close vicinity of each other. So we consider both quadrilaterals and triangles as possible regions for merging into a crossarm. The typical output of this separate detection is shown in Figs. 2e,3e, and the final output showing overlay of detected part of utility pole is shown in Figs. 2f,3f.

To reduce the search space, we sort all the detected trapeziums by the height of their bounding box. We then extrapolate their medial lines, since parts of both pole and crossarm that are detected may not be spatially intersecting. We then consider the longer trapeziums in sorted order, and try to locate, from the bottom of the sorted sequence, at least one trapezium as follows. This trapezium must have height less than 20% of the longer trapezium currently being considered, its centroid must be present within a short distance from the upper half of the pole and whose medial line intersects the medial line of the longer trapezium between 80° and 100°. By careful observation, one can clearly see that though the crossarm and pole are perpendicularly mounted, this perpendicularity is only in 3-D space. In the worst case, given the distance between a ground observer, and the crossbar being mounted far away in the air at 20+ meters, the 2-D projection shows around 80° to 100° angle of intersection, as we observed from multiple ground truth images. The first composite shape showing such perpendicularly placed trapeziums is deemed as the utility pole. Any other structure like this may also be another pole, but we deem that as being part of background, and terminate our search after first detection of such composite shape.

$$Pole \;=\; \{L_i, L_j \in \{Long\,Trap.\}:$$

$$Angle\{L_i\} = Angle\{L_j\} \approx 90°\} \quad (3)$$

IV. Experiments and Data Collection

A standard Canon 12 MP f/2.8 RGB camera was used for imaging. The frame size was shortened to 1280×960 for testing purposes. We went out in rural regions, to get anomaly data. Poles embedded in soil in rural areas are prone to tilting, since the soil beneath can move and reshape easily. Poles exhibiting any kind of occlusion were specifically imaged, again to complicate the test dataset. Finally, anomalous poles were not found in one long stretch, but are randomly located in various different kind of geographical regions, as expected. Hence the background of all such images is highly variable, other than being heterogeneous. Also, the images were taken at different times of day, so that photometric and shadow issues are also variable. All such scenarios were considered because we are interested in demonstrating robustness of our algorithm, against different kind of variations. We could collect upto 20 such images, other than 127 images of normal/upright poles.

In our prior published research on detection of other power grid components, we did acquire long aerial videos and tested the algorithm's performance (only) on them. In the case of utility poles, we are still awaiting a widespread disaster event within our country, where we can try go and collect more data with structural problems in the object of interest (utility pole).

V. Results and Analysis

We implemented our algorithm in OpenCV language, and tested on the dataset mentioned before. We focus on the performance analysis of our algorithm on the poles with fault, since that is the objective of our application. In lack of any public dataset for this application, it is not possible to compare our work with work of other authors directly. Hence we studied prior literature, and picked up a promising algorithm, [9]. We compared the performance of their algorithm against our algorithm on *our* dataset. Further, we have also observed the *absolute* performance of our algorithm in general. Implementation of our algorithm is available from authors on request.

Since we are more interested in shortlisting of keyframes, and then only in highlighting the pole region, our ground truth consists of set of 212 frames that contained utility poles, whether erect or leaning. In terms of absolute performance, our algorithm is able to detect the poles in 70% of cases. In 95% cases, our algorithm detected some pole-like object, and in 5% cases, it missed the detection altogether. From the angle of *binary classification*, one can see that this amounts to a *precision* measure of *0.95*, and *recall* measure of *0.67*. Thus one can see that the performance of our algorithm is reasonable. However, when we compare its performance to existing work, we show that performance of our algorithm is in fact superior.

On running the program corresponding to [9], we found that it could only detect pole-like object in 60% of the images, and crossarms in *none*. Thus one can trivially compare and observe that the *recall* measure of this algorithm, even assuming that its precision measure being ideal i.e. 1, will be less than the recall of our algorithm. Specially with images in which pole region has some degree of occlusion, the method of [9] fails often. This performance can be attributed to the complexity of images our dataset has, versus the complexity of their images as visible in the paper. The images used by them mostly have a close-in view of the pole top, and hence most of the background is sky only. Also, due to zoom in, the length of the partial pole imaged is not very short than the length of the crossarm in their dataset. For our dataset, their algorithm is missing detection of crossarm since its relative length is too less, and hence the corresponding peak in transform domain is insignificant compared to peak that of the pole. Looking this way, on realistic images provided by end customers, our algorithm gives a far superior performance.

A. Complexity Analysis

The complexity of mean-shift stage can be as low as $O(n)$ [3]. Next, classical feature-based blob extraction in has known complexity of size of graph, i.e. $O(n^2)$. Extraction of both quadrilaterals and trapeziums are contour-based methods. Hence their complexity is of order of image boundary, i.e. $O(n)$. Iterative merging of trapeziums considers a local window/block, as a candidate for merging. Given constant grid size, its complexity is of order of $O(n^2)$. Similarly, due to working in a neighboring window, the context-based recognition of pole, via identifying a crossarm near the top of a long trapezium, also has a complexity of $O(n^2)$. In summary, the overall complexity of the algorithm is bounded by $\mathbf{O(n^2)}$, which is acceptable for computation over a handheld device.

VI. A portable Deployment

Since power supply may not be available around disaster time, we tested our algorithm's deployment feasibility on battery-operated portable devices also. Specifically, we ported the algorithm on a resource-constrained device, Motorola Moto G XT running Android OS v 4.4.1 to test field-worthiness. A GUI-based application is developed, on lines of those discussed in [20] and [21], that can help operators/supervisors to get surveillance data and perform analysis on it. The application synchronizes to a surveillance database, may be hosted using Wi-Fi hotspot, via a wireless link/WLAN, and downloads a selected video. The application starts with an authentication screen, and the database can be synchronized only by authorized users. A set of assigned/unassigned videos to an authorized operator then get displayed. The operator can choose any of the videos, the selection of which leads to automatic running of our algorithm and creation of a set of keyframes, highlighting the detected part. These keyframes are then presented to the operator one-by-one for his study, as in Fig 4. The app was also ported and tested of another smartphone, Samsung Galaxy Note NT, running same OS.

VII. Conclusion and Future Work

Automatic detection of utility poles is a practically useful research problem, with application in disaster recovery. In

Fig. 4: A Screenshot of Operator's Application

this paper, we have proposed an algorithm of detection of poles in complex and heterogeneous outdoor surroundings. The algorithm deals with shape and orientation as prominent features of pole model. To do so, we extract candidate trapeziums, some of which represent parts of the pole. To overcome the missed detection of certain parts due to common problems of occlusion and diffusion into background, we propose a novel shape growing algorithm, that extrapolates and captures a longer trapezium representing the pole. The region growing stage is driven by orientation-based clustering of trapeziums. The entire algorithm was tested on many anomalous images collected by going into rural regions. It was found to exhibit reasonable performance via minimum presence of both false positives and false negatives. Especially it shows much better true detection of poles, than other known works. In future, we will like to improve handling of weak edges, and subsequent contour leak [22]. Also, from the part of a pole surface detected via shape considerations, we will try to extrapolate in shape-projected neighborhood using appearance considerations, e.g. template matching, so as to maximally detect pole-face. Overall, we believe that our algorithm for pole detection is robust enough with good performance, and hence can be extended and made applicable for detecting all standard types of poles in any other outdoor surroundings as well.

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