An Algorithm for Radar Power Line Detection with Tracking

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Abstract—In this paper we deal with the problem of power line detection from millimeter-wave radar video. We propose an algorithm that is based on Hough Transform, Support Vector Machine, and particle filter tracking. We explore the defining characteristics of the power lines in the radar video, and present an approach to utilize these characteristics together with the temporal correlation property of the power line objects. The particle filter framework naturally captures the temporal correlation of the power line objects, and the power-line-specific feature is embedded into the conditional likelihood measurement process of the particle filter. Experimental result validates the effectiveness of the power line detection approach.

I. INTRODUCTION

For the flight safety of helicopters, power-line-strike accident has been a substantial threat [5]. Most of these accidents happened at night, thus an automatic power line detection and warning system for helicopters that can work anytime is highly desirable to ensure helicopter flight safety. A few previous works have been developed for power line detection with radar [1][8][10]. However, these works provide no automatic algorithm to detect the power lines from the radar signal.

In [4], a power line imaging system based on a 94-GHz active millimeter-wave radar is reported. Unlike previous radar systems, the system in [4] can synthesize the field-ofview scene containing the power lines from the Intermediate Frequency (IF) channel of the reception signal in real time at 10 fps (frames-per-second). In Fig. 1 we show an example of a radar image and in Fig. 2 the zoom-in views of the power lines.From the radar images a few characteristics of the power lines can be observed. Firstly, although in these images the power lines appear as curves, it is just an artifact of the B-scope, i.e., polar coordinate view. They will appear as straight lines when the coordinate system is transformed to Cartesian coordinate. Secondly, the power lines appear in parallel groups. Thirdly, the power lines have a so-called Bragg pattern, i.e., the periodic peak pattern, due to the periodic pattern of the power line surface. Based on the synthesized field-of-view, the automatic detection of the power lines can be accomplished by an image processing approach on the radar video.

We have proposed an algorithm for automatically detecting power lines from the radar video in [7]. Hough Transform is employed to detect power line candidates, and a pre-trained Support Vector Machine (SVM) classifier is used to differentiate power lines from noise lines based on the power-line-



Fig. 1: B-scope image of a scene that contains power lines and their supporting towers.



Fig. 2: Zoom-in view of the power line images. The ground return noise is evident in the right image.

specific Bragg pattern. However, each frame is processed separately, and the important temporal correlation between power line object is only imposed as a heuristic post-processing step. Thus, even though the frame-level detection accuracy (determining if a frame contains power lines or not) in [7] is impressive, the power-line-level accuracy (determining the existence of individual power lines) is not as good.

In this paper, we observe that the temporal correlation of the power line objects can be captured by using formal tracking methods such as particle filtering. Particle filter has been applied to various tracking tasks such as tracking sports players [11], pedestrians [2], and surveillance applications. To the best of our knowledge, this paper is the first one to apply particle filter for tracking power lines in radar video. We demonstrate that the characteristics of the power lines can be embedded into the update step of the particle filter. The two distinguishing characteristics of the power lines, namely, the intrinsic characteristics or features of the objects, and the temporal correlation of the objects, are combined and both are effectively used. The successful usage of these two types of information is the key to the accurate and robust detection of the power lines.

In the next section, we explain our proposed approach in details. We present the experimental results in section III, and conclude this paper in section IV.

II. POWER LINE TRACKING WITH PARTICLE FILTER

A. Object Tracking with Particle Filter

The problem of object tracking can be modeled as the estimation of the hidden state of a system \mathbf{x}_k using a sequence of noisy measurements $\mathbf{z}_{1:k}$, where k is the frame index. The system state includes the information about the object of interest, such as the position, velocity, and the size of the object. Particle filter is a sequential importance sampling (SIS) technique to approximate the posterior pdf $p(\mathbf{x}_k | \mathbf{z}_{1:k})$ using a finite set of N weighted samples $\{\mathbf{x}_k^i, w_k^i\}_{i=1\cdots N}$ by Monte Carlo simulation. The candidate particles $\tilde{\mathbf{x}}_k^i$ are sampled from an appropriate importance distribution $q(\mathbf{x}_k | \mathbf{x}_{1:k-1}, \mathbf{z}_{1:k})$, and the weights of the samples are [3]

$$w_k^i = w_{k-1}^i \frac{p\left(\mathbf{z}_k | \tilde{\mathbf{x}}_k^i \right) p\left(\tilde{\mathbf{x}}_k^i | \mathbf{x}_{k-1}^i \right)}{q\left(\mathbf{x}_k | \mathbf{x}_{1:k-1}, \mathbf{z}_{1:k}\right)}$$
(1)

In the case of bootstrap filter [9][12], the importance distribution $q(\mathbf{x}_k|\mathbf{x}_{1:k-1}, \mathbf{z}_{1:k})$ is the same as the state transition density $p(\mathbf{x}_k|\mathbf{x}_{k-1})$, and the weight w_k^i for each particle *i* in frame *k* is then simplified as

$$w_k^i = w_{k-1}^i \cdot p\left(\mathbf{z}_k | \tilde{\mathbf{x}}_k^i\right) \tag{2}$$

Because a large number of these particles have negligible weights, the particles are re-sampled in each frame to avoid the degeneracy problem. For a fixed number of particles initialized with equal weight, the importance weight in Eq. 1 is reduced to $p(\mathbf{z}_k | \tilde{\mathbf{x}}_k^i)$, the conditional likelihood of a new observation \mathbf{z}_k given the particle $\tilde{\mathbf{x}}_k^i$.

B. Cascaded Particle Filters

We observe that the state vector can often be decomposed into a few un-correlated sub-states, and the state space can be decomposed into a few orthogonal sub-spaces. Let $\mathbf{x}_k =$ $(\mathbf{u}_k, \mathbf{v}_k)$, if we have \mathbf{u}_k and \mathbf{v}_k independent of each other, i.e., $p(\mathbf{x}_k) = p(\mathbf{u}_k, \mathbf{v}_k) = p(\mathbf{u}_k) \cdot p(\mathbf{v}_k)$, it can be easily shown that $p(\mathbf{x}_k | \mathbf{z}_{1:k-1}) = p(\mathbf{u}_k | \mathbf{z}_{1:k-1}) \cdot p(\mathbf{v}_k | \mathbf{z}_{1:k-1})$, and $p(\mathbf{x}_k | \mathbf{z}_{1:k}) \propto p(\mathbf{u}_k | \mathbf{z}_{1:k}) \cdot p(\mathbf{v}_k | \mathbf{z}_{1:k})$, i.e., both the prediction and update steps can be factored into the prediction and update of \mathbf{u}_k and \mathbf{v}_k separately. For particle filter, the dynamic model to propagate the particles can be defined separately in the sub-spaces, and the measurement likelihood $p(\mathbf{z}_k | \tilde{\mathbf{x}}_k^i)$ is thus decomposed into individual measurement likelihood in the sub-spaces, i.e., $p(\mathbf{z}_k | \tilde{\mathbf{u}}_k^i)$ and $p(\mathbf{z}_k | \tilde{\mathbf{v}}_k^i)$.

C. Observation Models

In this paper, we propose to track the power lines in the Hough Transform domain using cascaded particle filters. The power line is represented by two parameters, θ and ρ in the Hough Transform domain, and they are very much independent. Another reason for separating θ and ρ is because in reality we find that all the power lines in the field-ofview captured by the radar are parallel, thus the θ value for all the power lines are the same. θ can be estimated first, then individual ρ values for individual power lines can be further estimated by individual ρ trackers along the estimated θ direction. Thus, according to the cascaded particle filters in the previous section, we will consider two separate likelihood measurements, $p(\mathbf{z}_k | \tilde{\theta}_k^i)$ and $p(\mathbf{z}_k | \tilde{\rho}_k^i)$.

1) Observation Model for θ , $p(\mathbf{z}_k | \tilde{\theta}_k^i)$: It it defined as the following:

$$p(\mathbf{z}_k|\tilde{\theta}_k^i) = \underbrace{c(\mathbf{z}_k|\tilde{\theta}_k^i)}_{\text{concentration}} \cdot \underbrace{s(\mathbf{z}_k|\tilde{\theta}_k^i)}_{\text{line strength}} \cdot \underbrace{g_{\theta}(\tilde{\theta}_k^i, \hat{\theta}_{k-1})}_{\text{temporal smoothness}}$$
(3)

Adopting the preprocessing algorithm including thresholding and coordinate transformation in [7], Hough Transform converts a frame \mathbf{z}_k to Hough-domain data $H_k(\theta, \rho)$, and $H_k(\theta_i, \rho_j)$ represents the number of pixels (or line strength) for a particular line parameter combination (θ_i, ρ_j) . It can be shown that $\sum_{\rho} H_k(\theta_1, \rho) = \sum_{\rho} H_k(\theta_2, \rho)$ for any θ_1, θ_2 , yet $H_k(\theta_1, \rho)$ and $H_k(\theta_2, \rho)$ have different distributions over ρ . For the true power line orientation, $H_k(\theta_{true}, \rho)$ is more concentrated because there are a few power lines with the same θ_{true} . With a similar concept as entropy, we define the "concentration" measure as:

$$c(\mathbf{z}_k|\tilde{\theta}_k^i) = \sum_{\rho} H_k(\tilde{\theta}_k^i, \rho) \log \left(H_k(\tilde{\theta}_k^i, \rho) \right) \Big|_{H_k(\tilde{\theta}_k^i, \rho) > 0}$$
(4)

For the true power line orientation, there will be a few lines with significant strength. The line strength measure $s(\mathbf{z}_k | \tilde{\theta}_k^i)$ takes the sum of the top three values in $H_k(\tilde{\theta}_k^i, \rho)$. Lastly, the temporal smoothing term for θ is defined as:

$$g_{\theta}(\tilde{\theta}_k^i, \hat{\theta}_{k-1}) = \exp\left(-(\tilde{\theta}_k^i - \hat{\theta}_{k-1})^2 / 2\sigma_{\theta}^2\right)$$
(5)

where $\hat{\theta}_{k-1}$ is the tracked θ in the previous frame and σ_{θ} is the standard deviation parameter of the Gaussian function.

2) Observation Model for ρ , $p(\mathbf{z}_k | \hat{\rho}_k^i)$: The ρ tracker is cascaded after the θ tracker and tracks for the ρ value of each individual power line along the orientation $\hat{\theta}_k$ tracked by the θ tracker. The conditional likelihood of a particular ρ sample $\tilde{\rho}_k^i$ is defined as:

$$p(\mathbf{z}_k | \hat{\rho}_k^i) = \underbrace{f(\mathbf{z}_k | \hat{\rho}_k^i)}_{\text{classifier confidence}} \cdot \underbrace{a(\tilde{\rho}_k^i, \hat{\rho}_{k-1})}_{\text{association function}} \cdot \underbrace{g_{\rho}(\tilde{\rho}_k^i, \hat{\rho}_{k-1})}_{\text{temporal smoothness}}$$
(6)

The classifier confidence is directly inherited from the SVM classifier in [7]. The association function measures the similarity of the Hough domain data in a local neighborhood between

this sample $\tilde{\rho}_k^i$ and the tracked $\hat{\rho}_{k-1}$ in the previous frame, using a normalized correlation function. Lastly, the temporal smoothing term for ρ is defined in the similar way as Eq. 5:

$$g_{\rho}(\tilde{\rho}_{k}^{i}, \hat{\rho}_{k-1}) = \exp(-(\tilde{\rho}_{k}^{i} - \hat{\rho}_{k-1})^{2}/2\sigma_{\rho}^{2})$$
(7)

D. Power Line Detection with Tracking

The motion dynamic models that propagate the particles are defined as drifting models considering that the movement of the helicopter is smooth:

$$\theta_k = \theta_{k-1} + \varepsilon_\theta \tag{8}$$

$$\rho_k = \rho_{k-1} + \varepsilon_\rho \tag{9}$$

The process noise ε_{θ} and ε_{ρ} are drawn from zero-mean Gaussian distributions with standard deviations of σ_{θ} and σ_{ρ} .

The θ -tracking algorithm is presented in the following, the purpose of which is to estimate the orientation of all the parallel power lines in a frame given the orientation of the power lines in previous frame:

Algorithm 1 The θ -tracking algorithm

Input: A new radar video frame \mathbf{z}_k , and its Hough Transform $H_k(\theta, \rho)$ if k = 0, i.e., the first frame then $\hat{\theta}_0 = \arg \max_{\theta} c(\mathbf{z}_0|\theta) \cdot s(\mathbf{z}_0|\theta)$ Initialize N_{θ} θ -particles $\tilde{\theta}_0^i = \hat{\theta}_0$, $w_{\theta_0}^i = \frac{1}{N_{\theta}}$ else Propagate θ -particles according to Eq. 8 Measure weight according to Eq. 3, $w_{\theta_k}^i = p(\mathbf{z}_k|\tilde{\theta}_k^i)$ Output $\hat{\theta}_k = \arg \max_i w_{\theta_k}^i$ Re-sample N_{θ} un-weighted particles from $p(\theta_k|\mathbf{z}_{1:k})$ approximated by $\{\tilde{\theta}_k^i, w_{\theta_k}^i\}$ end if Output: $\hat{\theta}_k$

The re-sampling step is implemented in the same way as [6]. The algorithm for processing a ρ -tracker is:

Algorithm 2 The ρ -tracker processing algorithm

Input: A new radar video frame \mathbf{z}_k , its Hough Transform $H_k(\theta, \rho)$, the output $\hat{\theta}_k$ from θ -tracker, and the particles of the ρ -tracker $\{\tilde{\rho}_{k-1}^i, w_{\rho_{k-1}}^i\}$ from previous frame **Propagate** ρ -particles according to Eq. 9 **Measure** weight according to Eq. 6, $w_{\rho_k}^i = p(\mathbf{z}_k | \tilde{\rho}_k^i)$ **Output** $(\hat{\rho}_k, w_{\hat{\rho}_k}) = \arg \max_i w_{\rho_k}^i$ **Re-sample** N_ρ un-weighted particles from $p(\rho_k | \mathbf{z}_{1:k})$ approximated by $\{\tilde{\rho}_k^i, w_{\theta_k}^i\}$ **Output:** $\hat{\rho}_k, w_{\hat{\rho}_k}$

The overall power line detection with tracking algorithm is presented in Alg. 3. T_{ρ} is a parameter that controls the association threshold for the ρ -tracker, and M_{ρ} defines the maximum number of ρ -trackers allowed in each frame. In the first frame the ρ -trackers are initialized by searching for

Algorithm 3 The power line detection with tracking algorithm

Input: A new radar video frame \mathbf{z}_k Step 1. Pre-process: thresholding and coordinate transformation according to [7] **Step 2.** Hough Transform: $\mathbf{z}_k \to H_k(\theta, \rho)$ **Step 3.** θ -tracking: get $\hat{\theta}_k$ by Alg. 1 **Step 4.** *ρ*-tracking if k = 0, i.e., the first frame then **Initialize** M_{ρ} ρ -trackers by searching for M_{ρ} local maxima $\{\rho_{0,j}, j = 1, \cdots, M_{\rho}\}$ in $H_0(\hat{\theta}_0, \rho)$. for all $\rho_{0,i}$ do if $f(\mathbf{z}_k|\rho_{0,j}) > 0$, i.e., passes SVM then Initialize N_{ρ} particles $\tilde{\rho}_{0,j}^i = \rho_{0,j}$ else Terminate this ρ -tracker $\rho_{0,j}$ end if end for else **Process** each ρ -tracker $\rho_{k,j}$ by Alg. 2, get the ρ -tracker output $\hat{\rho}_{k,j}$ and $\hat{w}_{\rho_{k,j}}$ if $\hat{w}_{\rho_{k,j}} > T_{\rho}$ then Keep this ρ -tracker else Terminate this ρ -tracker end if Add new ρ -trackers by searching for local maxima not covered by any ρ -tracker, similar to k = 0 initialization case, and allow up to M_{ρ} ρ -trackers end if **Output:** $(\hat{\theta}_k, \hat{\rho}_{k,j})$ in each ρ -tracker as detected power lines in \mathbf{z}_k

local maxima in Hough data, which is the same way for detecting power lines as the previous algorithm [7]. If a line candidate (corresponding to a local maximum in Hough data) is classified by the SVM as a power line, a ρ -tracker is initialized and it continues to track its position in future frames. If the detection result is inaccurate and it is actually a false alarm power line, the tracker will most likely not be able to find any good association in future frames and this false alarm ρ -tracker will be terminated. When a power line is occluded by noise, the tracker could lose track of it. To recapture it when the power line appears again, in each frame we also search for candidate power lines in the region that is not covered by any ρ -tracker and initialize new ρ -trackers.

III. EXPERIMENTS

The helicopter flight test team has collected 8 datasets, each lasting from a few seconds to about 15 seconds. These datasets are collected under different flying conditions and they can represent most of the cases that happen in real-world situations. The simulation is carried on using these datasets. We compare the line-level detection results in Table I with the previous power line detection algorithm in [7]. We manually inspect the result for each frame, and compute the line-level

TABLE I: Power-line-level recall and precision comparison with previous algorithm.

	[7]		Ours	
Dataset	Recall	Precision	Recall	Precision
1	75.87%	58.13%	97.73%	91.51%
2	79.06%	76.68%	97.91%	97.84%
3	73.78%	81.17%	87.45%	99.85%
4	57.29%	77.59%	79.57%	94.29%
5	77.72%	92.55%	80.69%	91.01%
6	46.15%	45.08%	100.0%	90.64%
7	57.37%	50.13%	94.78%	91.75%
8	50.26%	63.23%	89.65%	84.81%
Overall	68.36%	68.94%	92.03%	92.83%

TABLE II: Power-line-level recall and precision comparison with θ -only tracking.

	θ -only		$\theta + \rho$	
Dataset	Recall	Precision	Recall	Precision
1	84.64%	91.59%	97.73%	91.51%
2	92.56%	100.0%	97.91%	97.84%
3	84.88%	99.83%	87.45%	99.85%
4	61.88%	92.70%	79.57%	94.29%
5	77.92%	85.90%	80.69%	91.01%
6	93.86%	94.31%	100.0%	90.64%
7	90.69%	88.31%	94.78%	91.75%
8	64.68%	75.31%	89.65%	84.81%
Overall	79.86%	90.47%	92.03%	92.83%

recall and precision for each dataset. We can see that with the proposed cascaded particle filter tracking algorithm, both recall and precision are greatly improved, thus boosting the robustness of the power line detection algorithm significantly.

To validate the necessity for cascaded θ -tracking and ρ tracking, in Table II we compare the line-level recall and precision with the θ -only tracking algorithm. In each frame the overall power line orientation is tracked, and the top M_{ρ} lines along that direction are classified by the SVM classifier as power lines or noise lines. We can see the performance with full $\theta + \rho$ tracking algorithm is superior to that of θ only. We notice that the involvement of ρ -trackers particularly improves the recall, which means more true power lines can be detected. The reason is that without the ρ -trackers, power lines that are occluded by the ground return noise may not be correctly classified by the SVM, thus they are missed by the θ -only algorithm. But with the ρ -tracking algorithm, the strong association of these partially occluded power lines between neighboring frames can still be greater than T_{ρ} , thus the effective utilization of temporal correlation complements the "blind spots" of the SVM classifier.

We show some visual results in Fig. 3. The power lines are overlaid as red lines in the detection results. We can clearly see the effectiveness of the the algorithm.

IV. CONCLUSION

In this paper, we present a robust detection with particle filter tracking algorithm to automatically detect power lines from the video captured by a 94 GHz millimeter-wave radar. The



Fig. 3: Some example frames with power line detection results. Notice these are zoom-in views showing the power line region only.

particle filter framework captures both the power-line-inherent features and the important temporal correlation feature. The experimental results show that the algorithm has superior performance over the previous power line detection algorithm. The power line imaging radar and the detection algorithm in this paper can provide a valuable assistance to helicopter pilots to avoid power-line-strike accidents, especially under poor visibility and at night.

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