Analysis of Imageless Ground Scene Classification Using a Millimeter-Wave Dynamic Antenna Array

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Abstract—We present an analysis of the capability for imageless ground scene classification using a rotationally dynamic millimeter-wave antenna array. The concept is based on the detection of signal artifacts generated by artificial objects in a scene, which manifests in the Fourier, or spatial frequency, domain. Man-made, artificial structures, such as buildings and roads, are generally characterized by sharp edges, which generate spatial frequency responses that are confined to a narrow angular range but extend over a broad spatial frequency bandwidth. These artifacts can be detected by generating a ring-shaped filter in the Fourier domain, which can be obtained through the novel design of a linear antenna array with rotational dynamics. We discuss the design of a millimeter-wave linear dynamic array for generating ring-filters and analyze the ability of such an array to classify ground scenes containing artificial structures from those without when mounted on an aerial platform, such as a drone. We compare ring filter designs and explore the use of a heuristic classifier and the K-nearest neighbor (K-NN) classifier on a large dataset of microwave ground scenes obtained from a database. Using a single ring filter that can be implemented with a two-element antenna array, small classification errors of 0.6%–3.2% were observed. Implementing multiple filters in a linear array consisting of four elements reduced the error to 0.3%.

Index Terms—Classification, dynamic antenna array, interferometric imaging, linear sparse arrays, microwave imaging, radar imaging, spatial frequency.

I. INTRODUCTION

CLASSIFICATION of scene information is important in a broad range of civilian and military remote sensing applications. Due to the abundance of information obtained from remote sensing systems, both from satellites and aerial platforms, methods of rapidly classifying scenes are of primary interest so that relevant information can be efficiently processed. Microwave and millimeter-wave sensing systems make up a significant portion of the sensing systems employed [1]–[4]. These systems are of particular interest since the wavelengths are sufficiently long that signals propagate through clouds, fog, and other obscurants with negligible attenuation yet are sufficiently short that high-resolution imagery can be obtained. These advantages make microwave and millimeter-wave systems ideal for applications such as remote sensing [5]–[7] and imaging [8], [9]. Various sensing applications, from sensing the Earth’s surface via aerial platforms to distant security imaging of people, require differentiation between naturally occurring and artificial structures/objects [10]–[14]. To effectively determine whether man-made structures/objects exist in the scene of interest, image-based classifiers are typically implemented where the classification performance is dependent on the measurement, signal processing, and the selected classifier in combination with the evaluated features. Each of the stages contributes to the overall cost in terms of hardware and the associated computational complexity. Interestingly, imagery often contains more than the required minimum information for effective classification results, which means that unnecessary resources can be committed to the collection and processing of redundant or unnecessary data. Understanding this phenomenon, the designs associated with both the measurements (hardware and acquisition time) and the processing can be optimized to reduce system complexity and cost by eliminating resources that would have been designed for unnecessary tasks.

Typically, remote scene classification is approached separately from the data acquisition process. The remote sensing system acquires data and forms a set of images, which are then passed to a classification algorithm that operates on the image data. Many works have focused on classifying a large number of images using image processing approaches. Various features can be obtained from images, such as target sizes, geometries, and/or edges of structures/objects, which can be leveraged individually or in combination to perform classification on the imaged scene [15]. Recently, machine-learning-based techniques have been applied to this approach to address the sheer amount of data that must be processed [16]–[19]. Such approaches, however, necessitate full image reconstruction for every scene of interest leading to a significant amount of data that must be acquired, transferred, and processed before classification takes place, which can strain resources in hardware, communications, and computational processing.

In this article, we investigate the use of a novel approach to obtain a small subset of the spatial frequency information in a scene using a rotationally dynamic millimeter-wave antenna array and demonstrate the ability to classify scenes containing...
man-made structures with only a small amount of data compared to a full imaging system. The approach only samples a ring of spatial frequencies in the Fourier transform domain of the scene spatial intensity, capturing the unique spatial frequency signatures of man-made objects. In contrast to other approaches, the presented technique does not sample sufficient information to reconstruct a full image; however, this leads to a significant reduction in the amount of information necessary for scene classification and, furthermore, may be beneficial for privacy-preserving applications. We recently proposed a novel two-element dynamic antenna array concept where a two-element interferometric antenna array was designed with rotational spatiotemporal dynamics to acquire filtered spatial frequency domain information [20]–[22], which focuses on features that are particular to man-made shapes in the scenes. The concept uses the dynamic rotational motion of the array, which is far simpler than typical mechanically steered imaging systems and, thus, assumes that the scene is quasi-stationary during the measurement. In this work, we explore the design of a millimeter-wave antenna array for obtaining filtered spatial frequency information from ground scenes and evaluate the classification capabilities using filtered spatial frequency data from a publicly available microwave remote sensing database. We compare ring filter designs and explore the use of a heuristic classifier and the K-nearest neighbor (K-NN) classifier on a large dataset of microwave ground scenes obtained from the database. Using a single ring filter that can be implemented with a two-element antenna array, small classification errors of 0.6%–3.2% were observed. Implementing multiple filters in a linear array consisting of four elements reduced the error to 0.3%. Other than remote sensing, the dynamic antenna array concept can be implemented for applications such as contraband detection and other short-range sensing use cases.

II. DYNAMIC ANTENNA ARRAY DESIGN FOR FILTERED SPATIAL FREQUENCY SENSING

Interferometric imaging systems coprocess the signals received at elements in a sparse array to generate high-resolution imagery with a fraction of the aperture area required in typical imaging systems. Pairwise cross correlation of the received signals generates spatial frequency samples (Fourier-domain information) of the scene to be reconstructed [23], [24]. The spatial frequency domain is commonly referred to as the visibility $V(u, v)$, where $u$ and $v$ represent the two dimensions of the domain. The smallest unit of a typical interferometric array is a two-element array (see Fig. 1) where the spatial frequency being sampled corresponds to a far-field sinusoidal pattern dependent on the baseline separation $D_1$ between the two antennas [see Fig. 1 (top)] and the orientation formed between the baseline and the system’s horizontal plane [see Fig. 1 (bottom)]. A ring-shaped spatial frequency filter can be synthesized by dynamically rotating the array at a fixed baseline [20]. Four rotation points are shown in Fig. 1, along with the sampled visibility points in the Fourier transform of an image for a ring filter of radius $D_1$ cycles/rad.

The concept for the dynamic antenna array combines the interferometric technique and rotational array dynamics to sparsely sample spatial frequency information. By implementing the dynamic spatiotemporal modulation on a simple linear antenna array, additional spatial frequency filters can be obtained simultaneously, while far fewer elements are needed to achieve adequate scene classification compared to other millimeter-wave imaging approaches. The dynamic linear antenna array concept is shown in Fig. 2 where eight interferometric correlation pairs are shown in different colors. Each pair forms a different baseline, synthesizes a spatial
frequency ring filter through rotational dynamics, and, thus, captures unique features in the spatial frequency spectrum.

While the visibility sampling process occurs at the receiver, both passive and active interferometric remote sensing systems have been demonstrated for various applications, such as space-borne remote sensing or short-range concealed contraband detection. An accurate sampling of the visibility requires the received radiation to be incoherent in space and time [23], [24]; this is satisfied for signals that are intrinsically generated by the scene via thermal means [23], [25]–[27] but can also be supported by the active transmission of incoherent signals from multiple transmitters [28]–[30], the latter also helping to improve the system sensitivity.

A. Spatial Frequency Sampling

The scene visibility is the 2-D Fourier transform of the scene intensity \( I(\alpha, \beta) \) and is given by [23], [24]

\[
V(u, v) = \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} I(\alpha, \beta) e^{j2\pi(u\alpha + v\beta)} d\alpha d\beta
\]  
(1)

where \( \alpha \) and \( \beta \) are the direction cosines defined as \( \alpha = \sin \theta \cos \phi \) and \( \beta = \sin \theta \sin \phi \), respectively. The spatial frequency sampling function \( S(u, v) \) is defined by the electrical separations (baselines) of the elements in the antenna array, the reconstructed scene intensity can then be calculated by the sampled visibility by

\[
I_r(\alpha, \beta) = \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} V(u, v) S(u, v) e^{-j2\pi(u\alpha + v\beta)} du dv.
\]  
(2)

For a sparse array comprising a discrete set of antenna elements, the set containing all discretely sampled spatial frequency information is given by

\[
S(u, v) = \sum_{n=1}^{N} \sum_{m=1}^{M} \delta(u - u_n) \delta(v - v_m)
\]  
(3)

where \( \delta(\cdot) \) is the Dirac delta function and the quantity \( N \times M \) represents the maximum number of spatial frequency sampling points for an interferometric antenna array. The 2-D Fourier transform of the sampling function yields the array point spread function. The product between the visibility and the discrete sampling function is the sampled visibility \( V_r(u, v) = V(u, v) \cdot S(u, v) \), and the reconstructed scene intensity \( I_r \) can be found by

\[
I_r(\alpha, \beta) = \sum_{n=1}^{N} \sum_{m=1}^{M} V_r(u_n, v_m) e^{-j2\pi(u_n\alpha + v_m\beta)}.
\]  
(4)

The field-of-view (FOV) of an interferometric imager is determined by the spatial frequency sampling rate [3]. In one dimension, a spatial frequency sampling interval \( \delta u \) yields ambiguities in the point spread function at intervals of \( \delta u^{-1} \); thus, the reconstructed image will be ambiguous in space at the same interval spacing. If the sampling interval is too wide, the image ambiguities may overlap. This can be avoided by ensuring that the ambiguities fall outside the FOV, which can be given by the half-power beamwidth of the antennas \( \theta_{HP} \), assuming that all antennas have identical patterns. The sampling interval can then be determined by \( \delta u \geq (1/\theta_{HP}) \). If the desired FOV is sufficiently narrow, high-gain antenna elements can be used.

Scene classification can operate on the reconstructed intensity \( I \) via image processing means as described above. The approach in this work, however, is to operate directly on the sampled visibility \( V_r(u, v) \) without reconstructing the image and, furthermore, with very little spatial frequency information. In fact, our approach uses an amount that is insufficient for full image reconstruction, thereby allowing privacy-preserving detection and classification. The dynamic array approach has the added benefit of reducing the hardware requirements compared to conventional imaging approaches; high-gain steered-beam systems use either a large, filled aperture (e.g., a reflector antenna) or an electronically steered phased array, which necessitates the use of many antenna elements along with their associated transceiver hardware. Conventional interferometric arrays already reduce hardware burdens by eliminating beam scanning to realize larger synthesized apertures using comparably fewer antennas as in traditional phased arrays and/or focal-plane arrays [24], [32]–[37]. By implementing appropriate array dynamics, the number of antennas required can be further reduced as a larger physical array can be dynamically synthesized over time through antennas’ movements.

B. Spatial Frequency Features Captured by Array Dynamics

Imageless classification via the dynamic antenna array concept is based on capturing spatial frequency features present in the scene. In particular, the objective is to distinguish remote sensing images of nonnatural scenes (NNSs) comprising man-made structures, such as roadways and/or bridges from remote sensing images of natural scenes (NSs) containing only natural landscapes. Man-made structures generally have sharp edges, which are infrequent in NSs and that manifest strong spatial frequency signals that are localized to spatial frequency angles orthogonal to the edge direction in the spatial domain and extend radially outward over a broad spatial frequency bandwidth. Five examples of NS and NNS radar images from [31] with a spatial FOV of 1000 m \( \times \) 1000 m and a resolution of 1 m/pixel are shown in Fig. 3. Examples of the visibility for an NS and an NNS are shown in Fig. 4(a) and (b) along with their corresponding visibility in Fig. 4(c) and (d). Note that the visibility is not generally affected by topology since range information is not obtained. The visibility of the NS shows smoother spatial frequency content, whereas the NNS visibility presents strong while discrete components that are orthogonal to the direction of the sharp edges. Since these spatial frequency features are largely discrete and directional, they enable detection with only a small subset of the available visibility information. One such way is to synthesize a ring filter in the spatial frequency domain [20], as shown in Fig. 5, where a two-element dynamic array is rotated regarding its centroid covering a spatial frequency bandwidth over the full 360° of the \( uv \)-plane. Since the filter covers the full angle of rotation, discrete spatial frequency features that extend
radially outward can be captured. Note that this approach only requires the correlation pair to rotate 180° due to the symmetric nature of the visibility, and the direction of rotation is arbitrary. As discussed in [20], a design may be implemented by rotating an array on an aerial vehicle’s rotor blades where the two antennas always remain copolarized enabling the dynamic array to operate either actively or passively as described earlier. We previously demonstrated the ability to detect Fourier-domain features of simple reflecting objects using a millimeter-wave dynamic antenna array [22], [38].

Accounting for the rotational dynamics of the array, the effective dynamic spatial frequency sampling function $S_d$ is obtained by modifying (3), yielding

$$S_d(u, v) = \sum_{k=0}^{K-1} \delta(u - u_{rk})\delta(v - v_{rk})$$

(5)

where $K$ is the total number of sampled angles among the 180° rotation and

$$u_{rk} = D_r \sin \gamma(k)$$

(6)

$$v_{rk} = D_r \cos \gamma(k)$$

(7)

Fig. 5. Example of utilizing a dynamically rotated correlation pair to synthesize a spatial frequency ring filter. Physical separation of $D_r$ will yield a ring filter with a radius of $D_r$ cycles/rad. The radius of the ring filter is also dependent on the center frequency (red circle), and the extending coverage of spatial frequency bandwidth is dependent on the antenna bandwidth (yellow). A 180° rotation from the correlation pair covers the full 360° span on the uv-plane, indicating that no reset is required, and a continuing rotational dynamics will synthesize additional ring filters. The direction of rotation is a design choice.
Fig. 6. (a)–(d) Simulated scene examples of size 1000 m × 1000 m demonstrating common dimensions of man-made structures. (e)–(h) Corresponding normalized visibilities are below each scene example. The spatial bandwidth as formed by the edges is inversely proportional to the spatial frequency bandwidth of the associated features. When multiple man-made structures of different dimensions exist in the same scene, a single ring filter implementation (shown with the white dashed circles) might not detect spatial frequency features outside of the sampled bandwidth motivating the investigation of utilizing multiple ring filters that can be achieved by a dynamically rotated linear antenna array. (i)–(l) Corresponding processed ring-filtered $S_r(\gamma)$ from (9), synthesized with a baseline of $161\lambda$ over the entire 360° $uv$-plane. N.U.: Normalized units.

where $D_r$ represents the available baselines formed by the linear array and $\gamma(k)$ can be expressed by

$$\gamma(k) = \gamma_0 + \gamma_r k \tau$$

(8)

using the initial angle of the dynamic linear antenna array $\gamma_0$, the rotational rate $\gamma_r$, and an integration time $\tau$ for each spatial frequency sample.

C. Dynamic Linear Array for Multiple Ring Filters

The design of the ring filter should consider the visibility of the objects of interest. Shown in Fig. 6 are a set of simulated targets of common dimensions for man-made structures, simulated using the FOV and resolution of the radar images of Fig. 4, with their associated normalized visibility. As in 1-D Fourier transform where a rectangular function with pulsewidth $T$ is related to a sinc function with its main lobe residing across the frequency range $2/T$, the same applies to 2-D structures and their visibilities. As shown in Fig. 6(a) and (b), the effective spatial extent formed by the edges of a tennis court is much smaller than a football field, which explains how the spatial frequency bandwidth of the edge related responses is wider in Fig. 6(e) and narrower in Fig. 6(f). The inversely proportional relationship between the spatial extent and spatial frequency bandwidth is also demonstrated in Fig. 6(c), where spatial extent in the vertical direction is significantly greater than the horizontal direction of a four-lane highway meaning that the associated orthogonal visibility responses extend wider in the $u$-direction and diminishes faster in the $v$-direction. As demonstrated in Fig. 6(d), when multiple man-made structures appear in the same FOV, the radially extended outward spatial frequency features Fig. 6(h) can diminish at the spatial frequency region, which can make the design of a single ring filter implementation challenging. Thus, we consider utilizing multiple ring filters to improve the probability of observing these spatial frequency features by implementing a dynamically rotated linear antenna array. While individual object responses cannot generally be separated after filtering, the use of multiple filters does improve the likelihood of detecting responses from multiple different objects.
In [20], a single ring filter of baseline $761\lambda$ was heuristically determined and subsequently fed to a decision boundary-based classifier. The baseline decision not only considered the spatial–spectral signal length near $761 \text{ rad}^{-1}$ but also considered a notional implementation of a 40-GHz system on a medium-sized unmanned aerial vehicle (UAV) [39] matching the altitude and physical separation requirement of the single correlation pair that is close to a typical rotor blade assumption above although occlusion from the UA V body is not considered here. Furthermore, an antenna separation of 50 $\lambda$, $161\lambda$, $261\lambda$, $361\lambda$, $461\lambda$, $561\lambda$, $661\lambda$, and $761\lambda$ is also considered to approach a decision boundary. The baseline decision was based on a decision boundary-based classifier operating on a single ring-filtered output. The decision boundary was calculated based on the midpoint of the uncertainty range where the data in each ring-filtered response are transformed to a 1-D vector $S$, which is the average response spanning across the 360° of the $\text{u-v}$-plane, where $\gamma$ is the angle with respect to the positive $u$-axis, and is given by [20]

$$S(\gamma) = \frac{\sum_{r=M}^N V_t(r \cos(\gamma), r \sin(\gamma))}{N-M}$$

which yields the rate of change of the filtered data that better captures the discrete spatial frequency components. Finally, the mean of $S'$ is calculated to generate specific pattern for each of the 2076 sets of data, thus enabling a decision boundary to be defined to differentiate between NS and NNS. Examples of the ring-filtered responses using (9) for a ring filter synthesized at $161\lambda$ are shown in Fig. 7 for the real data of Fig. 4, and the simulated responses are shown in Fig. 6(i)–(l). The distributions of the derived patterns for NS and NNS are shown in Fig. 8 for all eight ring filters.

From the total dataset, approximately 70% of the images were used as the training set to determine the decision boundary, and the remaining approximately 30% were used as the testing set to evaluate the performance of the classifier. The decision boundary was calculated based on the midpoint between the two quantities maximum $\mu S'_{\text{NS}}$ and minimum $\mu S'_{\text{NNS}}$, where the former represents the NS pattern with the highest ring-filtered averaged responses and the latter corresponds to the NNS pattern with the lowest responses. To avoid biasing of evaluating the specific composition of the training and testing set, a total of 1000000 Monte Carlo simulations [41] were conducted where the data within the training and the testing sets were randomly reassigned between each iteration. To evaluate the performance of the classifier, the error rate (ERR) and the F1 Score (F1) [42], [43] are reported in the top half portion of Table II representing the averaged metrics from

### Table I

**Electrical Baselines Assuming 40 GHz and 3% Antenna Beamwidth**

| Physical Baseline | $-1.5\%$ | $+1.5\%$ |
|-------------------|----------|----------|
| $61\lambda$       | 60\lambda| 62\lambda|
| $161\lambda$      | 159\lambda| 163\lambda|
| $261\lambda$      | 257\lambda| 265\lambda|
| $361\lambda$      | 356\lambda| 366\lambda|
| $461\lambda$      | 454\lambda| 468\lambda|
| $561\lambda$      | 553\lambda| 569\lambda|
| $661\lambda$      | 651\lambda| 671\lambda|
| $761\lambda$      | 751\lambda| 771\lambda|

### Fig. 7

Example of ring-filtered responses, $S$, of Fig. 4(c) and (d) with a baseline of $161\lambda$ over the entire 360° of $\text{u-v}$-plane. N.U.: Normalized units.
The ERR is defined as the sum of the false positives and false negatives divided by the total number of samples and gives a measure of the total number of errors. The F1 is a measure of the accuracy of the classifier and is the harmonic mean of precision and recall, where the former is the ratio of the true positives to the sum of all classified positives and the latter is the ratio between the true positives and the sum of the true positives and false negatives. As observed, a 161\( \lambda \) ring filter performed the best on average with an ERR of 1.4% and an F1 of 98.6%.

### B. K-NN Classifier

While the decision boundary provided reasonable classification performance, it only utilizes a single pattern from each scene type within the training set. For a two-class classification problem with a large training set of \( N \) patterns, \( N - 2 \) patterns will be discarded, which is not efficient utilization of the training patterns. However, using all available patterns is equally problematic as outliers can affect the outcomes for the decision boundary resulting in overfitting; hence, the K-NN classifier was selected as an alternative to improve the classification performance by evaluating multiple training patterns that are locally closed to each of the incoming unknown patterns for classification. The K-NN classifier determines the class of an unclassified sample by examining the class label of the K-nearest known patterns from the training set, where the final classification is based on the vote of the majority class among the K-NNs [15], [44].

All eight ring filters were evaluated using a K-NN classifier where the nearest \( K = 37 \) patterns from the training set were used to determine the type of each pattern from the testing set. \( K \) was selected as an odd integer for \( K = \sqrt{K_{\text{training}}} \), where \( K_{\text{training}} \) is the total number of patterns in the training set (i.e., 737 NSs and 737 NNSs). For each the scenario, 100 Monte Carlo iterations were also performed, where the generation of training and testing sets was randomized between each iteration. The averaged K-NN classifier results are shown in the lower half of Table II, including the performance improvement (IMP) for the F1 metric. It is evident that the K-NN classifier outperforms the decision boundary approach for all eight scenarios with an averaged F1 improvement of 1.2% and significantly lower ERR where the best performing single ring filter of 261\( \lambda \) had an average ERR of 0.6%. We also note that the standard deviation of evaluated statistics is lower for the K-NN. The improvement by selecting the K-NN classifier was expected as using more patterns in the training set should contribute to the performance of the classification process. Similar to the decision boundary results, the performance differences among different baselines of ring filters are noted, which may possibly be due to the difference
in the number of structures manifesting spatial frequency responses that fall within the spatial frequency bandwidth of a single ring filter. Therefore, it is reasonable to assume that the classification results should be further improved by using a dynamic linear antenna array comprising multiple ring filters.

IV. ROTATIONAL DYNAMIC LINEAR ANTENNA ARRAY DESIGN AND OPTIMIZATION

The concept diagram of the rotational dynamic linear antenna array generating eight ring filters was shown in Fig. 2 where eight differently colored cross correlation pairs (i.e., 16 antennas) rotate around a common centroid (i.e., each individual pair’s centroid is the same as the full linear antenna array’s centroid). The implementation can be further optimized by removing redundant antennas [3], [45] from the linear antenna array such that the total required antennas can be reduced. However, this will require the center of rotation to be properly designed to ensure that circular spatial frequency sampling points can be synthesized. This design aspect is noted but not further expanded in this work. A summary of the discussed rotational dynamic linear antenna array concept and the associated antenna baselines is given in Table III.

To understand the effect of whether using multiple ring filters improves the classification performance, the sequential selection algorithms were utilized to determine the best $N$ ring filters combination where $N = 2, 3, \ldots, 7$. The selected sequential selection algorithms are the widely known sequential forward selection (SFS) and its reverse counterpart, the sequential backward selection (SBS) [46], [47]. Both SFS and SBS algorithms are suboptimal but efficient methods compared to an exhaustive search of optimal subset where the former obtains a subset of all the available features by adding locally the best feature during each iteration, and the latter seeks the same objective by removing locally the worst feature during each iteration. The two selected sequential selection algorithms were applied to the eight baselines in conjunction with the K-NN classifier where the objective function was to optimize the F1 metric of the classifier. The following sequential selection scenarios are performed: finding the best seven, six, five, four, three, and two baselines (ring filters) using the SFS and the SBS methods. In Tables IV and V, the 12 optimized dynamic linear antenna array designs are summarized with their corresponding ring filter combination. The associated K-NN classifier outcomes corresponding to the 12 scenarios covered in Tables IV and V are summarized in Table VI where SFS.Best$N$ and SBS.Best$N$ represent the best $N$ ring filters determined by the corresponding sequential selection algorithms.

It is evident that the performance outcomes of the K-NN classifier considering multiple baselines are all better than the best case for the single baseline case (i.e., $261\lambda$ using K-NN in Table II). An array with two baselines using SFS optimization (SFS.Best2 with ERR of 0.3% and F1 of 99.7%) obtained the best performance, while adding additional baselines either did not improve the performance, or when seven baselines were used, the performance began to degrade. This can be explained by the commonly known “curse of dimensionality” in classification analyses, where increasing the number of features in a classifier leads to better performance; however, the improvement at some point has diminishing returns, leading to minimal performance improvements for significant effort. Increasing the number of features can undermine the classifier performance when the dimension is too high (i.e., too many features) [15]. Therefore, it is desired to use only a subset of all available features while achieving reasonable classification performance. Furthermore, in the present case, reducing the number of features also leads to a reduction in the number of antennas required, further minimizing the hardware burden. As a comparison, all eight ring filters were selected in conjunction with the K-NN classifier where an ERR of 0.5% was obtained with an F1 of 99.5%, as shown in Table VI. As observed, while this also provides better performance compared to the single ring filter scenario (0.6% for $261\lambda$), the additional required hardware does not justify the small improvement compared to the optimized scenarios as determined by the sequential selection algorithms. As shown in Fig. 9, considering the original 16-antenna rotational dynamic linear antenna array as shown in Fig. 2, the optimized design requires only four antennas: two pairs to achieve $61\lambda$ and $261\lambda$. The optimized array design achieved an averaged ERR of 0.3% (half of the best performing single ring filter at 0.6%) and an averaged F1 of 99.7% where the cost of implementing

### Table III

| Baseline $D_\lambda$ | Antenna Pair |
|----------------------|--------------|
| $61\lambda$          | Pair1        |
| $161\lambda$         | Pair2        |
| $261\lambda$         | Pair3        |
| $361\lambda$         | Pair4        |
| $461\lambda$         | Pair5        |
| $561\lambda$         | Pair6        |
| $661\lambda$         | Pair7        |
| $761\lambda$         | Pair8        |
| Number of Antennas   | 16           |

### Table IV

| $61\lambda$ | $161\lambda$ | $261\lambda$ | $361\lambda$ | $461\lambda$ | $561\lambda$ | $661\lambda$ |
|------------|--------------|--------------|--------------|--------------|--------------|--------------|
| SFS.Best7  | X            | X            | X            | X            | X            | X            |
| SFS.Best6  | X            | X            | X            | X            | X            | X            |
| SFS.Best5  | X            | X            | X            | X            | X            | X            |
| SFS.Best4  | X            | X            | X            | X            | X            | X            |
| SFS.Best3  | X            | X            | X            | X            | X            | X            |
| SFS.Best2  | X            | X            | X            | X            | X            | X            |

### Table V

| $61\lambda$ | $261\lambda$ | $361\lambda$ | $461\lambda$ | $561\lambda$ | $661\lambda$ | $761\lambda$ |
|------------|--------------|--------------|--------------|--------------|--------------|--------------|
| SBS.Best7  | X            | X            | X            | X            | X            | X            |
| SBS.Best6  | X            | X            | X            | X            | X            | X            |
| SBS.Best5  | X            | X            | X            | X            | X            | X            |
| SBS.Best4  | X            | X            | X            | X            | X            | X            |
| SBS.Best3  | X            | X            | X            | X            | X            | X            |
| SBS.Best2  | X            | X            | X            | X            | X            | X            |
the two additional receiving antennas is a reasonable tradeoff for performance.

## V. Conclusion

In this work, we demonstrated that a dynamically rotated linear antenna array synthesizing multiple spatial frequency ring filters can be used for the classification of ground scenes in microwave remote sensing applications. We showed that the use of multiple ring filters from multiple antenna baselines yields better performance than single ring filter implementation using only one interferometric correlation pair. The K-NN classifier was selected as the classifier for the dynamic linear antenna array design as it performs significantly better than the decision boundary approach due to the fact it leverages more data points from the classification training set. Furthermore, a 16-element dynamic linear antenna array, eight correlation pairs synthesizing eight ring filters, was proposed as an initial design where all eight ring-filtered responses are leveraged for imageless classification directly in the spatial frequency domain. A classification-based optimization of the dynamic array design was made by using sequential selection algorithms to reduce the number of antenna pairs from the initial design while improving the classification performance.

A final optimized four-element rotational dynamic linear antenna array demonstrated an ERR of 0.3% that is at least half of the best performing single ring filter benchmark and that an additional antenna pair is a reasonable design consideration as the hardware burden is still significantly less than conventional imaging interferometric array. The proposed approach is amenable to implementation on aerial platforms, such as UAVs with rotating blades, and may provide a mechanism for fast classification of ground scenes without the data and processing requirements of traditional image classification approaches.

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