Angular Clustering of Millimeter-Wave Propagation Channels With Watershed Transformation

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Abstract—An angular clustering method based on image processing is proposed in this article. It is used to identify clusters in 2-D representations of propagation channels. The approach uses operations such as watershed segmentation and is particularly well suited for clustering directional channels obtained by beam steering at millimeter wave. This situation occurs for instance with electronic beam steering using analog antenna arrays during beam-training process or channel modeling measurements using either electronic or mechanical beam steering. In particular, the proposed technique is used here to cluster 2-D power angular spectrum maps. The proposed clustering is unsupervised and is well suited to preserve the shape of clusters by considering the angular connection between neighbor samples, which is useful to obtain more accurate descriptions of channel angular properties. The approach is found to outperform approaches based on K-power-means in terms of accuracy as well as computational resources. The technique is assessed in simulation using the IEEE 802.11ad channel model and in measurement using experiments conducted at 60 GHz in an indoor environment.

Index Terms—2-D angular measurements at 60 GHz, millimeter wave (mm-wave), propagation channel angular clustering, watershed transformation.

I. INTRODUCTION

Recent years have witnessed a growing interest in millimeter-wave (mm-wave) communications [1]. The spectrum congestion in the lower part of the spectrum and the ever-growing need of higher data rates incited the telecommunication actors to assess the suitability of mm-wave frequency bands to support gigabit-per-second wireless communications.

The channel can be then represented as a discrete dataset of features, such as power in a 2-D plane (azimuth and elevation angles), AoA/AoD information, full-digital antenna arrays or synthetic array [8], [9] are usually employed and algorithms, such as MUSIC [9], [10], SAGE [6], [8], [11], [12], or CLEAN [13], [14], can be used to estimate power, direction of arrival, and time-of-arrival (ToA) of multipath components. The channel can be then represented as a discrete dataset of features, such as power in a 2-D plane (azimuth and elevation angles) or a 3-D plane (both angles and ToA) [6]. Each sample in this discrete dataset can be modeled by a plane wave. This representation is then clustered and the probability density function (PDF) is fit to describe the behavior of intercluster and/or intraclass features, whether in angular domain or in time domain [16].

In mm-waves, analog antenna arrays are typically preferred over full-digital architectures or synthetic array to perform outdoor channel measurements in order to be able to benefit from the array gain before the analog-to-digital conversion of the baseband signal. The procedure is then to scan the whole angular range due to beam steering (either electronic [17] or mechanical [16]) or beam switching [17] and therefore obtain a quasi-continuous channel representation in the angular/frequency domain. The angular accuracy of this representation depends on the beamwidth of the antenna array and...
the angular step size. Based on this representation, regular
techniques can still be applied in time domain to obtain the
ToA discrete dataset, while high-resolution algorithms such as
MUSIC have been adapted to operate in such a beam space
representation [18] to estimate AoA/AoD and thus form the
discrete dataset [19] onto which classical channel modeling
procedures typically used in lower part of spectrum, including
clustering and PDF fitting, can be similarly applied [16].

Identifying cluster shapes in time domain is efficiently
performed using a priori knowledge, typically an exponential
decay with increasing delay [20]. While this assumption is
physically quite realistic, doing so to find clusters in the
angular domain, i.e., the power angular spectrum (PAS), is not
optimal as their shapes heavily depend on the scenario and the
environment. For instance, intracluster angular distributions
have been variously modeled in the literature by an exponential
decay in [21], a Laplacian distribution in [16] and [22], and
a von Mises distribution in [23]. Thus, there is still a need of
unsupervised clustering methods that preserve real cluster
shapes to more accurately describe channel features [24].
This is especially important to assess techniques that are
sensitive to PAS (see [25], [26] for AoA/AoD estimation
or [27] for multiuser power allocation in massive MIMO
context) or that use PAS as a priori knowledge (see [28]
for beam-training improvement or [29], [30] for AoA/AoD
estimation). Furthermore, the clustering method should be fast
enough since, to obtain statistically meaningful results, a large
number of channels are to be analyzed [24].

Most of the current propagation channel models in the
literature use the K-power-means (KPM) algorithm as the
clustering method [31]. The KPM algorithm is a modified
version of the general K-means [32] clustering method. K-means
aims to minimize the sum of the error between the centroid
and the components in all of the clusters, by minimizing
the average Euclidean distance between data points within a
cluster and the mean of the cluster, while KPM minimizes
the sum of power-weighted distances of parameter points to
the centroid associated with the parameter point [31], [33].
K-means-based cluster analysis has intrinsic weaknesses. First,
the number of clusters has to be assumed before the operation.
This implies to fix the number of clusters based on visual
inspection [34] or to use some automatic detection process
based on a priori knowledge [35]. However, it has been
observed in [36] that when different clusters exhibit different
statistics, the automatic detection may fail. Another approach
is an incremental search for that appropriate number, using
convergence threshold such as cluster power with respect to
total power [8], [37] or graphical-based metrics such as
silhouettes [38] for instance, albeit at the expense of higher
computational resources. Second, inappropriate initial clusters
lead to total power [8], [37] or graphical-based metrics such as
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computational resources. Second, inappropriate initial clusters
lead to local minima. To solve the initializing problem, the
K-means++ algorithm [39] was introduced to initialize the
centroid of the cluster randomly. Third and importantly for this
work, K-means-based methods are among globally clustering
methods and therefore treat all features equally, regardless of
the actual correlation among them. This third problem led to
the fact that the channel clusters do not reflect accurately the
channel impulse responses (CIRs) exponential decrease with
time in [20] and the CIR had to be fit with a priory known
exponential function to solve this issue [20]. However, a priory
function destroys the unsupervised nature of K-means. While
approaches have been proposed to weight differently features
in K-means, the weighting factors are often found empirically
and are scenario-dependent [40].

To address these shortcomings, this article introduces the
use of image signal processing techniques to obtain an efficient
and unsupervised approach for clustering channels in angular
domain that considers the connection between neighbor
samples. Indeed, not considering the location correlation may
result in faraway samples being grouped into the same angular
cluster, which jeopardizes preserving its actual shape. The idea
is not to work on the extracted features but directly on a quasi-
continuous channel representation in 2-D, namely, the PAS
along the elevation and azimuth angles. This allows for the
use of a set of morphological operations borrowed from image
processing to identify clusters while preserving their angular
shape. In particular, a watershed segmentation is performed
and the potential of this approach is assessed at 60 GHz with
simulations using the IEEE 802.11ad channel model and with
measurements in an indoor scenario. Section II describes the
considered scenario and the channel representation used in
this article. The proposed clustering algorithm is introduced in
Section III, while the performance is assessed in Section IV by
comparing the performance with KPM and a modified version
of KPM. The clustering method is validated with measurements
in Section V. Finally, Section VI draws conclusions and gives
some perspectives.

II. PROBLEM STATEMENT

To illustrate the clustering technique proposed in this article
as well as to assess its performance, the scenario shown in
Fig. 1(a) is considered. An omnidirectional transmitter
(TX) antenna and a directional receiver (RX) antenna with

Fig. 1. Generation of PAS. (a) Angular scanning. (b) Resulting 2-D PAS
grid in the azimuth–elevation plane.
a beamwidth ranging from 5° to 29° scan the 2-D angular space with a step fixed to 1°. This situation typically occurs in mm-wave while conducting channel modeling experiments with directional antennas [16], [17] or during beam-training process in mm-wave communications to find the strongest link, i.e., the strongest cluster, between a TX and a RX [41], [42]. A 2-D PAS is therefore obtained such as shown in Fig. 1(b). This quasi-continuous channel representation forms an image of pixels (i.e., the sampling cell) whose size depends on the angular step size and whose intensity, in grayscale, depends on the channel power in that particular direction. Imaging processing can therefore be applied to such PAS representation to perform efficient clustering. To generate such 2-D maps as a dataset onto which the clustering is performed, the IEEE 802.11ad directional channel model is used throughout this article [43], [44] for simulations. The IEEE 802.11ad is a standard for indoor wireless communication in the 60 GHz band. Its channel model is a time and angular cluster-based model. The scenario considered in this article is the conference room.

The PAS is obtained by the following formula:

\[
\text{PAS} = \int_0^T |g_r(\theta, \phi)g_t(\theta, \phi)h(t, \theta, \phi) + n(t)|^2 dt
\]

where \(h(t, \theta, \phi)\) is the CIR, \(g_r(\theta, \phi)\) and \(g_t(\theta, \phi)\) are the antenna gains of the TX and RX, respectively, and \(n(t)\) is the thermal noise, additive white Gaussian noise (AWGN). An example of noise-free PAS generated with a 5° RX beamwidth is shown in Fig. 2(a). The line-of-sight (LOS) component appears at \(\theta = \phi = 0°\), while clusters at other angles are due to reflections and diffractions within the environment. In actual measurements, in addition to thermal noise, spatial speckles are also present. They widely appear in images obtained by synthetic aperture radar (SAR) [45], laser [46], and mm-wave [47]. Speckles occur because of the stochastic coherent combination of a number of independent waves scattered in the environment. To model this effect, 100 speckles uniformly distributed in the angular plane are generated with identical power, equal to the PAS maximum power. This has been found empirically relevant with the experiments conducted and presented in Section V. The resulting PAS is shown in Fig. 2(b), where an AWGN of SNR = 20 dB is also added. Compared with the original PAS in Fig. 2(a), the background power is now higher and exhibits a weak fluctuation. Adding an AWGN in the CIR in (1) results in a spatial noise that follows a biased non-Gaussian distribution leading to a PAS mean SNR of 21.03 dB with a standard deviation of 4 dB. Speckles occupy single pixels. Both AWGN and speckles are to be removed to perform accurate clustering and using a simple threshold does not perform generally well. Section III shows how image-processing filtering techniques can remove them efficiently before performing clustering.

### III. Clustering Method

#### A. Morphological Operations for Watershed

Mathematical morphology (MM) is an imaging processing method to extract information based on set theory and lattice theory. A grayscale image is regarded as a function \(f(x)\) that maps a set of 2-D coordinate \(x\) (pixel position) to a 3-D surface extended to the third dimension (pixel value). In the situation in Fig. 1(b), the variable \(x\) is the discrete angle vector \((\phi, \theta)\), where \(\phi\) is the azimuth angle and \(\theta\) is the elevation angle. The function \(f(x)\) maps the whole angular plane to the received power, \(f(x): X^2 \rightarrow Y\). \(X^2\) and \(X^2\) is a 2-D coordinate set of the whole angular plane

\[
X^2 = \{x = (\phi, \theta) | \phi \in [-\pi, \pi], \theta \in \left[-\frac{\pi}{2}, \frac{\pi}{2}\right]\}. \tag{2}
\]

The generated 3-D space is defined with a set \(X^2 \times Y\)

\[
X^2 \times Y = \{(\phi, \theta, P) | \phi \in [-\pi, \pi], \theta \in \left[-\frac{\pi}{2}, \frac{\pi}{2}\right], P \in \mathbb{R}_+\}. \tag{3}
\]

The idea of MM is remodeling the 3-D space of an image with local functions, which are called structuring elements. A structuring element is also a mapping to angular plane, \(g(x): X^2 \rightarrow Y\), where \(X^2 \subseteq X^2\). The reconstruction performed in this article is achieved with some basic operations that are defined next.

**Operation 1:** Dilation \([48]\) \(f \oplus g : X^2 \oplus X^2 \rightarrow Y\) is used to extend the local spaces. It extracts the supremum of the sum of \(f\) and \(g\) at each sliding position of \(f\)

\[
(f \oplus g)(x) = \sup \{f(x-x') + g(x')\}. \tag{4}
\]

**Operation 2:** Erosion \([48]\) \(f \ominus g : X^2 \ominus X^2 \rightarrow Y\) is used to shrink the local image spaces. It extracts the infimum of the difference of \(f\) and \(g\) at each negatively sliding position of \(f\)

\[
(f \ominus g)(x) = \inf \{f(x+x') - g(x')\}. \tag{5}
\]
Operation 3: Opening [48] removes bright peaks that are small in size and break narrow connections between two bright peaks with dilation $\oplus$ and erosion $\ominus$

$$ f \circ g = (f \oplus g) \ominus g. \quad (6) $$

Operation 4: Closing [48] preserves small peaks that are brighter than the background and fills the small gaps between bright peaks with dilation $\oplus$ and erosion $\ominus$

$$ f \cdot g = (f \oplus g) \ominus g. \quad (7) $$

Operation 5: Euclidean distance transformation [49] $d(x, x')$ is an operation for a binary image. It assigns the value of each pixel $x$ in a subset $A$ of the whole image with the Euclidean distance between $x$ and the nearest nonzero pixel $x'$ inside a given connected domain $A$

$$ d(x, x') = \inf \left\{ \sqrt{\|x_i - x'_i\|^2} | A \subset X^2, x, x' \in A, P_A \neq 0 \right\}. \quad (8) $$

Operation 6: Geodesic distance [50] $d_A(x, x')$ is also on the plane $X^2$. It is the length of the shortest path linked two pixels $x$ and $x'$ in a connected space $A$ constructed by neighbor pixels with identical intensity level

$$ d_A(x, x') = \inf \left\{ \sqrt{\|x_i - x'_i\|^2} | A \subset X^2, x, x' \in A \right\}. \quad (9) $$

Operation 7: A geodesic ball [51] $\Omega_A(x, \lambda)$ with a center $x$ and radius $\lambda$ is defined as a domain set $x'$ whose geodesic distance $d_A(x, x')$ to $x$ is not larger than $\lambda$

$$ \Omega_A(x, \lambda) = \left\{ x' \in A \mid A \subset X^2, d_A(x, x') \leq \lambda \right\}. \quad (10) $$

Operation 8: Geodesic dilation [51] is the intersection between the geodesic ball $\Omega_A(x, \lambda)$ and a mark domain $B$

$$ \delta^\lambda_A(B) = \left\{ x' \in A \mid A \subset X^2, x \in A, \Omega_A(x, \lambda) \cap B \neq \emptyset \right\}. \quad (11) $$

Operation 9: Reconstruction [52] is a process of reshaping. If $f$ and $g$ are two grayscale images defined on the same domain and $f \leq g$, reconstruction iterates geodesic dilation $\delta^\lambda_x(f)$ until convergence

$$ \rho_g(f) = \sup_{\lambda > 0} \delta^\lambda_x(f). \quad (12) $$

Operation 10: Regional maxima [53] extracts a domain $D_{\text{max}}(f)$ of a difference between $f$ and reconstruction $\rho_f(f)$ with power tolerance $\varepsilon$

$$ D_{\text{max}}(f) = f - \rho_f(f - \varepsilon). \quad (13) $$

Operation 11: Laplacian filter [54] (second-order derivative field) is the difference between the external ($\nabla^+$) and internal ($\nabla^-$) gradients

$$ \nabla^2 f = \nabla^+ f - \nabla^- f \quad (14) $$

where

$$ \nabla^+ f = f \oplus g - f \quad (15) $$

$$ \nabla^- f = f - f \ominus g. \quad (16) $$

Operation 12: Zone of influence (IZ) [55], [56] $Z_{\text{IZ}}(K_i)$ is the subset of points in $X^2_i$ at a finite geodesic distance from the $i$th intersection domain $K_i$ and closer to $K_i$ than any other $j$th intersection $K_j$

$$ Z_{\text{IZ}}(K_i) = \left\{ x \in X^2_i \mid \forall j \neq i, d_{X_i}(x, K_j) < d_{X_i}(x, K_i) \right\} \quad (17) $$

where $K_i$ is the $i$th intersection domain between $X^2_i$ and $f(x)$, $K_i = f(x) \cap X^2_i$.

Operation 13: Skeleton by zone of influence (SKIZ) [55], [56] $S(K; G)$ is the complement set of all the IZ with

$$ S(K; G) = G - \bigcup_i Z_{\text{IZ}}(K_i). \quad (18) $$

B. Watershed Segmentation

Pixels are grouped into general segments $WS$ that are projection of a 3-D valleys in a field $f(x)$ onto a 2-D pixel plane. Valleys can be segmented between minima and around local maxima. Thus, watershed segmentation is to find the local minima centers and local maxima boundaries of clusters [55], [56]. It can be linked to a problem of damming watersheds at the maxima to avoid flooding the low basin. The domains enclosed by the watersheds are the target clusters. To achieve this aim, general watershed transformation algorithm in Algorithm 1 is used [55], [56]. A 3-D field $f(x)$ is cut by several angular planes $X^2_i$ at level $\lambda$. The intersections between $X^2_i$ and $f(x)$ are a set of domain $K$ in (17). While sweeping intensity levels from $\lambda_1$ to $\lambda_N$, the intersection domains $K$ are extended with reconstruction (12). When two $K$ contact each other, the bound is determined as SKIZ in (18), while the new intersections are IZ in (17). When reaching the maximum level $\lambda_N$, the target cluster set $W_N$ is obtained as the collection of final IZs, while the watershed set $WS$ is the complement of the clusters in the $X^2_i$ at $N$. The number of level $N$ is 255 for a grayscale image. In PAS clustering, $\lambda_N$ is the maximum of the function $f(x)$, while the choice of total level number, $N$, influences the running time of simulation.

In order to operate the watershed algorithm in Algorithm 1, power convex hill in Fig. 2 needs to be transformed to valleys. Therefore, the watershed transformation is here applied onto the Laplacian of the 2-D PAS, $\nabla^2 f$, as defined in (14). To be able to apply the water segmentation described in Algorithm 1, some pretreatment of PAS is as well as some extra steps to filter the speckles and fluctuations in Fig. 2(b) to avoid oversegmentation (i.e., artificially creating a too large number of clusters), as described in Algorithm 2. Step 1 removes speckles and partly smoothens the fluctuation caused by thermal noise. In step 2, the gradient field is obtained by the Laplacian operation and its contrast is enhanced in step 3. To mitigate the oversegmentation that typically occurs near the edge of clusters where the fluctuation of the Laplacian of the field is large, foreground and background markers are introduced. The foreground markers are the local maxima of the original PAS with (13), whereas the background markers are the curves equidistant to the clusters in the foreground with (8).

Figs. 3 and 4 show the process of obtaining the Laplacian gradient field. The result of despeckling and noise smoothing operations (step 1 in Algorithm 2) applied on the PAS in Fig. 2(b) is shown in Fig. 3(a). The speckles are well
Algorithm 1 General Flow of Watershed Segmentation

1: $W_1 \leftarrow \emptyset$, $\lambda_N \leftarrow \max f(x)$. 
2: for $i = 1$ to $N$ do 
3: \hspace{1em} $m_{i+1}(f) \leftarrow$ Equation (19) at level $\lambda_i$ with (12): 
4: \hspace{4em} $m_{i+1}(f) = \rho_{K_i}(K_i')$ \hspace{1em} (19) 
5: \hspace{4em} where $K_j = [X_i^2 \cap f(x)]_j$ \hspace{1em} (20) 
6: \hspace{4em} $K_i' = \left[ \bigcup_j K_j \right] X_i^2$ \hspace{1em} (21) 
7: 
8: end for 
9: $W_S \leftarrow$ Equation (23) as the final SKIZ 
10: where $W_S = W_{c_N} - W_N$ \hspace{1em} (23)
11: Retrun $W_N$ and $W_S$

Algorithm 2 Flow of Watershed Segmentation Solving Over-segmentation Problem

1: Despeckling and smoothing: remove isolated speckles with a combination of opening (6) and closing (7); smoothen the noised PAS with reconstruction (12) and average filtering.
2: Extract gradient field: calculate the curvature with the Laplacian filter $\nabla^2 f$ (14).
3: Enhance the contrast of gradient field: enhance contrast with closing (7); and reconstruction (12) and average filtering.
4: Extract the marks of foreground: get locations of $M$ regional power maxima of the foreground as centroid positions using (13) on the PAS within the interval of gradient level as tolerance $\varepsilon = \lambda_i - \lambda_{i-1}$.
5: Extract the marks of background: the marks are the curves equidistant to the domain with curvature in the PAS, which are the negative part of the Laplacian gradient field. The distances of every point in the background marker are calculated using (8) on the PAS directly.
6: Group clusters: combining the Laplacian field, marker of foreground and marker of background, operate the watershed segmentation with watershed transformation Algorithm 1.

removed. Furthermore, the PAS mean SNR has increased to 22.05 dB with a reduced standard deviation of 2.75 dB, showing that the noise has been smoothened. Then, the gradient field obtained by the Laplacian filtering (step 2 in Algorithm 2) is shown in Fig. 3(b). Expect for the LOS cluster, the edges of the other clusters are fuzzy and this may jeopardize the watershed transformation. Consequently, closing and reconstruction operations (step 3 in Algorithm 2) enhance the contrast and most of the valleys in the fields exhibit clear edges in Fig. 3(c).

Fig. 4 shows the results of the three remaining steps in Algorithm 2. Steps 4 and 5 are specifically introduced to avoid oversegmentation caused by the gradient field fast fluctuation in the vicinity of cluster edges. They introduce a constraint on IZ operation in the general watershed transformation of Algorithm 1. Step 4 creates markers of the illuminated foreground as local field maxima, as shown in Fig. 4(a). The number $M$ of local maxima is automatically found due to operation 13 and therefore does not need to be set a priori. Step 5 creates background markers with as shown watershed curves of the Euclidean distance field determined with (8) in Fig. 4(b). The foreground and background markers are the boundary of IZ operation domain: only the elements
Fig. 4. Results of Algorithm 2 at different steps. (a) Local maxima of original PAS as foreground markers. (b) Maximum distance curves as background markers. (c) Clusters marked with different colors.

between the foreground and background markers are effective to calculate IZ in (17). The clusters are finally obtained using watershed transformation in step 6 and are shown in Fig. 4(c).

The watershed transformation uses the combination of gradient field, foreground, and background. When two intersection domains between $X_2^2$ and $f(x)$, namely, $K_i$ for the valley marked with the foreground marker and $K_j$ for the valley outside the marked valley but enclosed by the background marker, contact with each other, two dual IZs are created by $K_i$ and $K_j$ with (17). All the marked valleys in the gradient field are segmented, while the valleys unmarked are neglected. Comparing the original PAS in Fig. 2(a) with the clusters in Fig. 4(c), it can be qualitatively observed that Algorithm 2 meets the original expectation of the proposed clustering approach. One important parameter is the shape of $g$ in (6) and (7) that influences the denoising and smoothing operation. $g$ is an $n \times n$ matrix forming an angular filter of a given shape (e.g., disk and square diamond), depending on the values of the elements of $g$ (0 or 1). In this study, a $3 \times 3$ square matrix is empirically found to perform well. Depending on parameters such as the angular step and the beamwidth, this operator may be adjusted to obtain the optimal performance.

C. Clustering Comparison: Modified KPM

To assess the performance of watershed, the 2-D PAS is also clustered with standard iterative KPM [31] in Section IV. Furthermore, in order to investigate the influence of the preprocessing steps in the modified watershed transformation introduced in Algorithm 2, similar steps are introduced in the standard KPM as another benchmarking method, named here modified K-power-means (modified KPM). In particular, fixed local maxima replace the iterative searching for centroids and opening and closing operations are used to remove the speckles. Furthermore, a threshold is used to remove the background whose value is selected using Otsu’s method [57]. Considering the sparsity of the mm-wave channel, the majority of PAS pixels represents the background rather than the clusters. Therefore, Otsu’s method extracts the power value $P_{back}$ of a PAS background by finding the pixel with highest probability in the intensity value histogram. The threshold $P_{thre}$ is then determined using the mean value $\mu_{SNR}$ and the standard deviation $\sigma_{SNR}$ of the SNR

$$P_{thre} = \frac{A(B+1)}{B(A+1)}P_{back}$$

where

$$10\log_{10}A = \mu_{SNR}[dB]$$

$$10\log_{10}B = \mu_{SNR}[dB] - 3\sigma_{SNR}[dB].$$

Here, the threshold is chosen three time higher than the mean SNR by a factor equal to three times the standard deviation $\sigma_{SNR}$ in order to remove 95% of the noise fluctuation. The flowchart of the modified KPM algorithm is shown in Algorithm 3. The multipath component distance (MCD) in the flowchart is the Euclidean distance used to evaluate the difference between individual multipath components. In this article, the $i$th parameter point is constructed with the azimuth $\phi$ and elevation $\theta$ as $(\phi_i, \theta_j)$. MCD between the $i$th and $j$th points is

$$MCD_{ij} = \sqrt{(\phi_i - \phi_j)^2 + (\theta_i - \theta_j)^2}.$$
Algorithm 3 Flowchart of Modified KPM Algorithm

1. Remove isolated speckles with a combination of opening (6); smooth the noised PAS with reconstruction (12).
2. Extract locations local maxima power as centroid positions $c_j(0), \ldots, c_K(0)$. Remove the isolated point noise with a combination of opening (6) and closing (7), then smooth it with restructuration (12).
3. Remove the background with a threshold $P_{thre}$ with Equation (24).
4. Assign MPCs to cluster centroids and store indices $I^{(i)}_l$:
   \[
   I^{(i)}_l = \arg \min_k \left\{ P_l \cdot MCD \left( x_i, c_k^{(l-1)} \right) \right\} \quad (27)
   \]
   \[
   I^{(i)} = [I^{(i)}_1 \ldots I^{(i)}_L], C^{(i)}_k = \text{indices} \left( I^{(i)}_l = k \right) \quad (28)
   \]
5. Return $R_k = [I^{(i)}, C^{(i)}_k]$

B. Qualitative Comparison Between Watershed and KPM

In order to study the influence of RX antenna radiation pattern on clustering, Fig. 5 shows the result of watershed segmentation for the PAS with beamwidths of $5^\circ$, $15^\circ$, and $25^\circ$. White closed curves are the labels for the identified clusters, i.e., the foreground domains. The dark blue domain is the background domain. Cluster labels clearly distinguish the adjacent foreground domains. Most of the power in the foreground is gathered into clusters, and the background with weak power intensity is clearly excluded from clusters. Intuitively, the watershed segmentation achieves the two main purposes of clustering: extracting the illuminated foreground from the dark background and distinguishing different illuminated domains. Furthermore, clustering can clearly be achieved with different beamwidths. Another important observation is that the cluster shapes are well preserved.

Using the standard KPM method, the entire angular space is divided into several polygons bounded by white straight lines, as shown in Fig. 6. In the example in Fig. 6(a), the illuminated foreground is roughly divided into large ranges, without distinguishing adjacent clusters accurately. Even worse, parts of the dark background are also enclosed into clusters. As the antenna beamwidth increases in Fig. 6(b) and (c), complete high-power-intensity regions are split and arranged into different clusters. The above phenomena manifest that the standard KPM method is not sensitive to the correlation between the adjacent regions. The shape of the cluster is not a polygon. Thus, the polygon division results in either the power leaking from a cluster into an adjacent one or the dark background being included into a cluster.

The result of modified KPM clustering is shown in Fig. 7. With a narrow beamwidth of $5^\circ$ in Fig. 7(a), most clusters of the illuminated foreground can be identified, and the dark background is eliminated. However, as the beamwidth increases to $15^\circ$ and $25^\circ$ in Fig. 7(b) and (c), respectively, the foreground markers do not improve the straight boundaries of the polygons in the standard KPM. The introduced foreground markers can find the location of certain clusters and thresholds can remove part of the background. However, part of the background is still enclosed into clusters, even in narrow beam transmission. In that case, the shapes of the clusters are only the shape of a uniform threshold instead of the individual cluster shapes. In the case of wide beam, the effect of threshold disappears: the adjacent clusters cannot be distinguished robustly.

C. Quantitative Performance Analysis of PAS Clustering

To assess the performance of the proposed clustering algorithm, several criteria are analyzed. First of all, the number of clusters is evaluated using the following ratio:

\[
\frac{\text{Number of estimated clusters}}{\text{Number of clusters generated by channel model}} \quad (29)
\]

This ratio is shown in Fig. 8(a). Some discrepancies between the estimated and generated number of clusters are naturally expected (i.e., the ratio (29) is not equal to 1). Since clusters’ mean angles are stochastically generated, clusters do overlap from time to time. However, it is interesting to notice that the three algorithms have the same trend.
beams provide higher angular resolution, so a larger number of clusters can be distinguished. As the beamwidth increases, the clusters become larger, and the corresponding number of clusters decreases. In wide beam transmission, the number of clusters provided by the watershed algorithm is closer to the number of channel clusters than the other two methods. It is also interesting to observe that all three algorithms overestimate the number of clusters when the beamwidth is narrow. Indeed, each cluster contains a few rays only, and for a given channel realization, a cluster can easily be interpreted as several clusters if the rays are angularly sparsely separated.

The second performance criteria evaluated are the separation between the foreground and background and can be assessed by the ratio of the power density of all clusters $C$ over the power density of the whole PAS plane (after despeckling and noise removing)

$$\frac{\iint_C P(\theta, \phi) d\theta d\phi}{\iint_{\text{PAS}} P(\theta, \phi) d\theta d\phi}$$

(30)

The performance is presented in Fig. 8(b). Since KPM cannot remove the background, the power of the entire PAS lies in the foreground, which is the sum of all clusters. Therefore, the ratio in (30) is one and is always one regardless of the beamwidth. After adding the threshold in the modified KPM method, the background is partially removed, and the ratio (30) increases. However, because background components cannot be entirely removed, some background power is also included in the cluster and the ratio is therefore not the highest. Watershed segmentation provides the most significant separation between the three algorithms. However, for wide antenna beams, the power density ratio decreases as the clustered power density is diluted into the background.

KPM and modified KPM often split clusters, which is an undesirable effect, and the integrity of clusters should be therefore assessed. To assess this effect, the metric used here is the ratio of the power in the preserved illuminated clusters over the power in the damaged illuminated clusters. Thus, the first step is to determine a practical definition of a preserved cluster. For continuous 2-D PAS map, the elements of a cluster are pixels, whose values depend on the power intensity within that cluster. A cluster is therefore a set of pixels with similar intensity compared with the neighbor domain. Because the
field is continuous and derivative, the second-order derivative field exists. Thus, a cluster is enclosed by the edge of a slope. Therefore, the edge is the elements pixels at the boundary with the highest second-order derivative. Because the intensity cluster is a continuous domain, the second-order derivative forms a continuous closed edge. Thus, the pixels inside this closed edge belong to a preserved cluster. Pixels belonging to cluster with discontinuous second-order derivative edge belong to damaged clusters. The following metric is subsequently defined as the ratio of the power $P(\theta, \phi)$ inside preserved clusters $C_p$ over the power inside damaged clusters $C_d$. As shown in Fig. 8(c), the ratio of watershed segmentation is close to one, which means that almost all the clusters are completely preserved. In contrast, the ratios of standard KPM and modified KPM are close to zero: the two clustering algorithms split most of the clusters.

Finally, the algorithm running time is assessed. Nowadays, with high-performance ray-tracing tools that exhibit reasonably realistic features, especially at mm-waves, they can be used for channel modeling to some extent [16], [58]. This approach involves a large number of channel realizations being generated and analyzed, generating a huge volume of data [24]. Consequently, a fast clustering method is highly desirable. The simulations have been performed with a laptop (CPU 2.60 GHz, RAM 8.00 GB) and the obtained logarithmic running time is shown in Fig. 8(d). When the beam is wide, the number of clusters decreases, so the required calculation time reduces. Standard KPMs take multiple iterations to avoid local minima, so it needs a simulation time of two-to-three orders magnitude more than the modified KPM or watershed segmentation. While iteration is not necessary for the modified KPM, it still needs to compute the random initial centroids, which is time-consuming. The watershed segmentation appears to be the fastest method among the three.

V. MEASUREMENT VALIDATION

A. Measurement Scenario

To verify the effectiveness of the angular clustering method, an experimental validation is conducted in a laboratory environment at Sorbonne University whose floor plan is shown in Fig. 9. The size of the room is approximately $10.25 \times 7.52$ m. The distance between the ground and the ceiling is 2.93 m. Measurements are randomly implemented in the zones that are marked as closed circles in Fig. 9. Both TX and RX are in the same zone for a given set of experiments with distance between TX and RX ranging from 0.5 to 2.5 m; 100 PAS samples are measured.

B. Measurement System

The measurement setup aims at emulating a beam-training strategy, as shown in Fig. 10. The TX antenna is an omni-directional dipole antenna with 2 dB gain, while the RX antenna is a directional horn antenna with a 24 dB gain. The beam-training strategy in Fig. 1(a) is achieved with RX angular scanning in the vertical and horizontal directions by an azimuth motor and an elevation motor with a $5^\circ$ angular step in both directions. The propagation channel is measured with a vector network.
TABLE I
PARAMETERS OF THE PURPOSED MEASUREMENT SYSTEM

| Parameter                  | Value            |
|----------------------------|------------------|
| Bandwidth                  | 8.64 GHz         |
| Related time resolution    | 0.12 ns          |
| Frequency sample number    | 752              |
| Frequency resolution       | 11.5 MHz         |
| Transmit power             | 4 dBm            |
| Noise level                | -100 dBm         |
| Dynamic range              | 103 dB           |
| Noise fluctuation of $S_{11}$ | 0.01 dB         |
| Rx beam width (E/H plane)  | 10.1°/13.1°      |
| Tx beam width (E/H plane)  | 360°/60°         |
| Tx antenna gain            | 2 dB              |
| Rx antenna gain            | 24 dB             |
| Angular sampling interval  | 5°               |
| Sampling range in azimuth  | [-180°, 180°]    |
| Sampling range in elevation| [-45°, 90°]      |

Fig. 11. Example of measured PAS in dB with (a) watershed segmentation-based clusters, (b) KPM-based clusters, and (c) modified KPM-based clusters.

C. Measurement Results

An example of measured PAS is shown in Fig. 11 along with clustering results of the three methods. Although not as good as in simulation, it can still be visually observed that watershed transformation grouped decently the clustered pixels in Fig. 11(a). The original KPM still fails to cluster the pixels, as shown in Fig. 11(b). Similar to simulations, modified KPM outperforms KPM and can cluster the pixels, as shown in Fig. 11(c). The overall lower performance compared with simulations is mainly due to the lower angular resolution of 5° step (few experimental attempts of 1°-step-size measurements have confirmed this hypothesis, but the measurement duration becomes then too prohibitive: three days for a single PAS).

The quantitative performance of clustering methods is shown in Table II. Similar to simulations, watershed segmentation still concentrates more energy as the power concentration ratio of 5.5, while the ratios of other two methods are much lower: 35.6% of the clusters are preserved with watershed transformation, which is much higher than 3.7% for modified KPM. Original KPM cannot preserve clusters at all. Watershed segmentation (0.035 s) runs little faster than modified KPM (0.067 s) and much faster than KPM (1.58 s). In summary, the result of measurement validates that watershed segmentation outperforms the other two methods.

VI. Conclusion

In this article, a method based on image processing is proposed to cluster 2-D angular channel representations. In particular, quasi-continuous PAS maps obtained by beam steering in azimuth and elevation are used as grayscale images onto which clustering is performed. It is shown that watershed transformation is more suitable than classical techniques to extract illuminated clusters from the dark background and to separate adjacent clusters in these 2-D maps. Furthermore, the proposed approach does preserve the shapes of clusters, which is a key criterion for performing accurate channel angular modeling. Using results obtained from 1000 realizations of the IEEE 802.11ad channel at 60 GHz, it has been shown that the proposed method significantly outperforms the KPM-based algorithm in terms of identified with respect to actual number of clusters, total channel power captured within clusters with respect to background, not splitting identified clusters, and computational resources. The method has also been validated with angular (both elevation and azimuth) channel measurements conducted in an indoor scenario at 60 GHz using mechanical beam steering.

Since the proposed approach operates on a PAS averaged over excess delay, it does not distinguish different time clusters with similar AoA. While the time dimension could be treated...
separately within already identified angular clusters, an interesting perspective consists in extending the proposed method to 3-D channel representations in order to achieve time–space clustering.

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