CLASSIFICATION OF POLARIMETRIC-SAR DATA USING FUZZY MAXIMUM LIKELIHOOD ESTIMATION CLUSTERING WITH CONSIDERATION OF COMPLEMENTARY INFORMATION BASED-ON POLARIMETRIC PARAMETERS, TARGET SCATTERING CHARACTERISTICS, AND SPATIAL CONTEXT

Katmoko Ari Sambodo*, Aniati Murni**, and Mahdi Kartasasmita*
* Lembaga Penerbangan dan Antariksa Nasional (LAPAN), Jl. LAPAN No. 70, Pekayon, Pasar Rebo, Jakarta, Indonesia.
** Faculty of Computer Science, University of Indonesia, Kampus UI Depok, 16424, Indonesia.
email: katmoko_ari@yahoo.com

ABSTRACT

This paper shows a study on an alternative method for unsupervised classification of polarimetric-SAR data. First, two feature extraction methods are performed in order to exploit the information of fully polarimetric-SAR data properly. One is based on derivation of features from polarimetric covariance matrix (totally nine parameters which represent each polarization power, polarimetric coherence, and polarimetric phase difference), and other is based on Cloude’s polarimetric decomposition (totally three parameters which characterize the target’s scattering mechanism). A feature reduction technique based on maximum noise fraction (MNF) transformation is then applied to these features to obtain most pertinent information and remove any redundant and other irrelevant information. Classification stage is then performed using fuzzy maximum likelihood estimation (FMLE) clustering algorithm. FMLE algorithm allows for ellipsoidal clusters of arbitrary extent and is consequently more flexible than standard fuzzy K-means clustering algorithm. However, basic FMLE algorithm makes use exclusively the spectral (or intensity) properties of the individual pixel vectors and spatial-contextual information of the image was not taken into account. Hence, poor (noisy) classification result is usually obtained from SAR data due to the presence of speckle noise. In this paper, we propose a modified FMLE which integrate basic FMLE (pixel-by-pixel basis) clustering result with spatial-contextual information by statistical analysis of local neighborhoods.

The proposed method has been tested on E-SAR polarimetric data acquired on the area of Penajam, East Kalimantan, Indonesia. Results obtained show classified images improving land-cover discrimination performance, exhibiting homogeneous region, and preserving edge and other fine structures.

Keywords: Polarimetric-SAR, unsupervised classification, polarimetric parameters and decomposition, wave scattering mechanism, maximum noise fraction (MNF) transformation, fuzzy maximum likelihood estimation (FMLE) clustering, spatial-contextual.

1 INTRODUCTION

Fully Polarimetric - Synthetic Aperture Radar (SAR) sensors are becoming more and more important in remote sensing applications due to: 1) its all-weather, day and night operational capability; 2) its sensitivity of the polarization state of the backscattered wave to physical characteristics of the ground target (e.g. shape, size, orientation, surface roughness, moisture content, dielectric properties of the target) [1], [2]. The utilization of multi-polarized wave in polarimetric-SAR system allows us to extract additional information which can be employed as classification features, thus giving better land use/cover classification results than single-channel single-polarization SAR data [1]-[3]. For this reasons, in recent years, the remote sensing community has become increasingly interested in the use of polarimetric-SAR data for the production of high accuracy land-cover maps.

Unsupervised classification is an important technique for automatic analysis of polarimetric-SAR data, since it can be performed regardless the availability of training dataset derived usually from ground truth information or other priori information about analyzed areas (which often both cost and time consumption). In the literature, many unsupervised classification approaches for polarimetric-SAR have been proposed. Basically, there are two types of algorithms: One type is based on the analysis of physical scattering properties,
which has the advantage that some information about class type is available [4]. Another type is based purely on statistical clustering of polarimetric-SAR data [5, 6]. Additionally, several interesting combinations of these types of classification approaches have been found [7]-[9].

These algorithms have been found to be applicable to land cover classification [10] and forest classification [11]. In general, acceptable classification results were obtained, however, in some cases, they also reported some limitations of these methods for further possibility to discriminate and classify into different object/land cover types especially with similar scattering mechanism and often yield clusters (classes) whose physical meaning is uncertain. To overcome these problems, it is advisable to use the additional information which can be included as extension input features thus reduce inter-class ambiguity and improve the classification performance [12], [13]. Although such additional information can be obtained from other data sources (such optical data, multi-frequency radar data, interferometric coherence, geological maps, etc), the consideration of additional information which can be extracted directly from same polarimetric-SAR data but using different aspect would be meaningful (such image texture, context, structural relationships, etc). However, most of these algorithms use a 3x3 complex covariance matrix (or coherency matrix) form as an input feature, thus other additional features (which usually represent as various data types) can not be added into this input form.

Another limitation of these algorithms is that they performed on a pixel-by-pixel basis, i.e., each pixel is treated independently of its neighbors; spatial context is only indirectly considered during speckle filtering. The local neighborhood does indeed have a significant influence on a pixel’s class membership. When a certain region already has already been classified, with high confidence, as belonging to a single class, it becomes comparatively unlikely that a pixel in this region belongs to another class. The much more likely scenario is misestimation of its covariance matrix due to speckle noise, which usually produced very noisy classification results (often appear as “salt-and-pepper” effect even in homogeneous areas). Due to inherently high noise level of SAR data, the inclusion of local neighborhoods in statistical decision about class membership is helpful to support homogeneous classification results [9], [14].

In this paper, we propose an unsupervised classification method based on fuzzy maximum likelihood estimation (FMLE) clustering algorithm that integrates complementary information of several polarimetric parameters and target scattering characteristic features, and spatial contextual information (see Fig.1). Fuzzy classification techniques allow each pixel in the image to belong to more than one cluster according to its degree of membership in each cluster [14]-[16]. Therefore, it is suitable for classification of SAR data as the presence of speckle noise often causes many pixels in the data are really ambiguous (i.e., imprecise, incomplete, and not totally reliable). A FMLE clustering has been chosen which it allows for ellipsoidal forms of the clusters and is consequently considerably more flexible than standard fuzzy K-means (FKM) clustering (with the use of Euclidean distance, thus giving circular clusters) [14]-[16]. Further advantage is that other features can be easily added into FMLE clustering process by extending the dimension of the input data vectors. These properties enable us to combine the wide range of information (features) which can be derived from polarimetric-SAR data using different feature extraction methods. In our case, motivate by our previous publication [13], we will combine a number of polarimetric parameters (polarization power, coherence, and phase difference) extracted from polarimetric covariance matrix and physical scattering characteristics of land use/cover based on Cloude’s polarimetric decomposition. These features have complementary information which can be integrated in order to improve the discrimination of different land use/cover types. To remove any redundant information and irrelevant information which may contain in these features, we apply a feature reduction scheme based on maximum noise fraction (MNF) transformation as a precursor step of FMLE classification.

However, the basic FMLE algorithm is a pixel-by-pixel basis classifier. Thus, in order to exploit the spatial-contextual information, we investigate the possibility of using probabilistic relaxation scheme. It iteratively adjust some initial estimates of the class-membership probabilities by reference to the class-membership probabilities of pixels in its neighborhood.

The proposed method has been tested on a fully polarimetric E-SAR (L-Band) data acquired on the area of Penajam, East Kalimantan, Indonesia.
2 FEATURE EXTRACTION SCHEMES

2.1 Polarimetric Data Representation and Polarimetric Parameter Feature Extraction

For radar polarimetry, the backscattering properties of the target can be completely described by a 2x2 complex scattering matrix, \( S \), such that

\[
S = \begin{bmatrix} S_{hh} & S_{hv} \\ S_{vh} & S_{vv} \end{bmatrix}
\]

(1)

where \( S_{hh} \) is the scattering element of horizontal transmitting and horizontal receiving polarization, and the other three elements are similarly defined. For the reciprocal backscattering case, \( S_{hv} = S_{vh} \).

Because there are effectively only three independent elements, the polarimetric scattering information can also be represented by a target vector, \( k = [S_{hh} \sqrt{2}S_{hv} S_{vh} S_{vv}]^T \) (where, the superscript “T” denotes the matrix transpose). The \( \sqrt{2} \) on the \( S_{hv} \) term is to ensure consistency in the span (total power) computation. A polarimetric covariance matrix \( C \) can be formed by [1]

\[
C = k k^T = \begin{bmatrix}
S_{hh} & S_{hv} & S_{vh} & S_{vv} \\
S_{hv} & S_{hv} & S_{vh} & S_{vv} \\
S_{vh} & S_{vh} & S_{vh} & S_{vv} \\
S_{vv} & S_{vv} & S_{vv} & S_{vv}
\end{bmatrix}
\]

(2)

where the superscript “*” denotes the complex conjugate.

\( C \) is a 3x3 Hermitian matrix, and has only six independent elements which can be employed as feature sets for classification purposes. Three real numbers on the main diagonal represent the powers (or intensity) of each polarization channels. The other three complex numbers on the off diagonal represent the complex correlations, which can be used to quantify the similarity of waves (or coherence) at different polarization. The magnitude of each complex number gives a measure of the degree of polarimetric coherence and lies between zero (incoherent) and one (completely coherent). The phase of each complex number represents the phase difference between two polarization states and lies between 0 and 180°. The degree of polarimetric coherence and polarimetric phase difference closely related to the physical characteristics of the target scene so it can be used as a feature set to discriminate different land-cover types [1].

2.2 Feature Extraction based on Cloude’s Polarimetric Decomposition

Fully polarimetric data provides unique possibility to separate scattering contributions of different nature, which can be associated to certain elementary scattering mechanisms (e.g. surface or single-bounce, double-bounce, and volume scattering). Several decomposition techniques have been proposed for extracting and identifying this valuable information. One method is based on polarimetric target decomposition theory proposed by Cloude and Pottier [4], which is capable of covering whole range of scattering mechanisms and yields an unsupervised classification scheme. The target’s scattering mechanism can be parameterized by entropy \( H \), anisotropy \( A \), and mean alpha angle \( \alpha \) which derived from the eigenvalue decomposition of the coherency matrix. (The coherency matrix is formed, similarly with the covariance matrix \( C \), but using the Pauli target vector \( \kappa = \frac{1}{\sqrt{2}} [S_{hh} S_{hv} S_{vh} S_{vv}]^T \)). The entropy \( H \), ranging from 0 to 1, represents the randomness of the scattering, with \( H = 0 \) indicating a single scattering mechanism (isotropic scattering) and
$H = 1$ representing a random mixture of scattering mechanisms. For ocean and less rough surfaces, surface scattering will dominate, and $H$ is near 0. For heavily vegetated areas, the $H$ value will be high, due to multiple scattering mechanisms. The anisotropy $A$ represents the relative importance of the second and third scattering mechanisms. A high anisotropy states that only the second scattering mechanism is important, while a low anisotropy indicates that the third scattering mechanism also plays a role. The mean alpha angle $\alpha$ reveals the averaged scattering mechanisms from surface scattering ($\pi \to 0$), volume scattering ($\pi \to 45^\circ$), to double bounce scattering ($\pi \to 90^\circ$). $H$ and $\alpha$ clearly characterize the scattering characteristics of a medium.

Cloude and Pottier further suggest an unsupervised classification scheme, using the $H-\alpha$ plane sub-divide into 8 basic zones characteristic of different scattering behaviors, as shown in Fig. 2. However, this unsupervised estimation of the type of scattering mechanisms may reach some limitations due to the arbitrarily fixed linear boundaries in the $H-\alpha$ plane which may not fit to data distribution, leading to noisy classification results [7], [11]. Hence, in this work, we use entropy $H$, anisotropy $A$, and mean alpha angle $\alpha$ directly as classification feature sets together with features extracted from first feature extraction method. To remove any redundant information and irrelevant information which may contain in these features, we apply the following feature reduction scheme as a precursor step of FMLE classification.

2.3 Feature Reduction based on Maximum Noise Fraction (MNF) Transformation

Classification of high-dimensional data is inherently difficult and generally high computational-cost. A feature reduction scheme is, therefore, needed to reduce the number of input features by removing any redundant information and irrelevant information from the complete feature space as a precursor step of classification process. For this purpose, in this paper, we use the maximum noise fraction (MNF) transformation. This transform have been commonly used, especially in the study of hyperspectral data, to determine the inherent dimensionality of image data, to segregate noise in the data, and to reduce the computational requirements for subsequent processing [14], [17]. The MNF transform is essentially two cascaded principal components (PC) transformations. The first transformation, based on an estimated noise covariance matrix, decorrelates and rescales the noise in the data. This first step results in transformed data in which the noise has unit variance and no band-to-band correlations. The second transform is a standard principal components transformation of the noise-whitened data. The inherent dimensionality of the data is then determined by examination of the final eigenvalues and the associated images. The data space could be divided into two parts: one part associated with large eigenvalues and coherent eigenimages, and a complementary part with near-unity eigenvalues and noise-dominated images. In this work, the noise covariance is estimated from a homogeneous area of the original (input) feature datasets. The idea of extracting noise covariance in this way is based on the assumption that the backscattering properties of radar signal should exhibit similar characteristics over the homogeneous area, thus any variations in the measured values can be viewed as a noise.

3 PROPOSED FUZZY MAXIMUM LIKELIHOOD ESTIMATION (FMLE) CLUSTERING INCLUDING SPATIAL CONTEXT

There have been many different families of fuzzy clustering algorithms proposed in the last decade. In this paper, a fuzzy maximum likelihood estimation (FMLE) clustering has been chosen which it allows for ellipsoidal forms of the clusters and is consequently considerably more flexible than standard fuzzy K-means (FKM) clustering (with the use of Euclidean distance, thus giving circular
clusters) [14]-[16]. Further advantage is that other features can be easily added into FMLE clustering process by extending the dimension of the input data vectors. These properties enable us to combine the wide range of information (features) which can be derived from polarimetric-SAR data using different feature extraction methods, as described in previous section.

3.1 Fuzzy Maximum Likelihood Estimation Clustering (FMLE) Algorithm

Let \( X = \{ x_1, x_2, ..., x_n \} \) be the input features set which is consists of \( n \) vectors \( x_i \in \mathbb{R}^d \) ( \( d \) is dimension of input features). Assuming there are \( K \) clusters (classes), \( \mu_i = \mu_i(x_i) \in [0,1] \) is the membership of the \( i \)-th sample \( x_i \) in the \( k \)-th cluster. Each sample point \( x_i \) satisfies the following two constraint

\[
\mu_i \in [0,1] \quad \text{and} \quad \sum_{k=1}^{K} \mu_{ik} = 1, \quad k = 1...n
\]

(3)

The probability of cluster \( k \) is given by

\[
P(k) = \frac{m_k}{n} = \frac{\sum_{i=1}^{n} \mu_{ik}}{n}, \quad k = 1...K
\]

(4)

The cluster means \( \mathbf{m}_k \) and covariance matrices \( \mathbf{s}_k \) can then be written in the form

\[
\mathbf{m}_k = \frac{\sum_{i=1}^{n} \mu_{ik} x_i}{\sum_{i=1}^{n} \mu_{ik}},
\]

\[
\mathbf{s}_k = \frac{\sum_{i=1}^{n} \mu_{ik} (x_i - \mathbf{m}_k)(x_i - \mathbf{m}_k)^T}{\sum_{i=1}^{n} \mu_{ik}}, \quad k = 1...K
\]

(5)

These moments in turn determine the membership probabilities according to \( u_{ik} = P(k | x_i) \), the posterior probability \( P(k | x_i) \) for cluster \( k \) given the observation \( x_i \). That is, invoking Bayes’ Theorem and assuming each cluster to have a multivariate normal density distribution, we have

\[
u_{ik} = P(k | x_i) = cP(k)P(x_i | k) = cP(k)\frac{1}{\sqrt{2\pi}} \exp \left[ -\frac{1}{2} (x_i - \mathbf{m}_k)' \mathbf{s}_k^{-1} (x_i - \mathbf{m}_k) \right]
\]

(6)

where \( c \) is a normalization constant independent of \( \mathbf{k} \) which can be determined from (3). Starting from some initial choice of the memberships \( \mu_{ik} \), the FMLE algorithm consists of a simple iteration of Equations (3-6) until convergence.

Because of the exponential distance dependence of the memberships in Equation (6), the algorithm is very sensitive to initialization conditions, and can even become unstable. To avoid this problem, we follow the suggestion of Gath and Geva [16] and first obtain initial values for the \( \mu_{ik} \) by preceding the calculation with the FKM algorithm. For this purpose, in this work, we use only the entropy \( H \) and mean alpha angle \( \alpha \) features to obtain initial \( \mu_{ik} \). However, the eight zones (or classes) in the \( H-\alpha \) plane are not applied here, instead, we determine the number of classes based on the image content and a ground survey information.

3.2 Spatial-contextual Information based on Probabilistic Relaxation

The FMLE clustering algorithm described above make use exclusively the spectral (or intensity) properties of the individual pixel vectors and spatial-contextual information of the image was not taken into account.

In order to incorporate spatial-contextual information in classification process, in this paper, we adapted the probabilistic relaxation scheme. This idea is based on the assumption that two neighboring pixels are not entirely statistically independent: In reality, spatially random classification results are not very likely, instead continuous areas of certain sizes are to be expected. It seems clear that information from neighboring pixels should increase the discrimination capabilities of the pixel-based measured data, and thus, improve the classification accuracy and the interpretation efficiency. Such ancillary information can be expressed by a neighborhood function \( q_r \), which must somehow reflect the contextual information of the neighborhood [9], [14]. In order to define it, a compatibility coefficient \( P(x,y,r) \) is introduced, i.e., the conditional probability that pixel \( x \) falls into class \( k \), if a neighboring pixel \( y \), belongs into class \( r \). As mentioned before, \( K \) possible class assignments are possible; furthermore it is possible to incorporate a larger neighborhood consisting of \( L \) pixels. Based on this, a neighborhood function

\[
q_{ik}(x) = \sum_{r=1}^{K} \sum_{i=1}^{L} P(x,k,y,r)P(y,r)
\]

(7)

can be defined, which describes the total joint probability over all neighbours and their class assignments, that a pixel \( x \) falls into class \( k \). The
probability \( q_{\mu_i} = q_i(x_i) \) gives information about class membership of pixel \( x_i \) solely by examination of its neighborhood and without considering content of the pixel itself.

After the FMLE clustering procedure, the class membership probabilities (according to Equation 6) are known. This allows to evaluate Equation (7) and results in two kinds of class probabilities for each pixels: One, \( q_{\mu_i} \), based only on spatial-contextual information, and another, \( q_{\mu_j} \), based on spectral information only. A combined spectral-spatial class membership is then determined by

\[
\mu(x_i) = \frac{\mu_j q_{\mu_i}}{\sum_{j=1}^{K} \mu_j q_{\mu_i}}
\tag{8}
\]

In our case, the compatibility coefficient is estimated from the initially classified image (result of pixel-by-pixel basis FMLE clustering).

Alternatively, this probabilistic relaxation procedure can also be iterated arbitrarily often by applying Equations (7) and (8) iteratively. In this work, we will observe the influence of number of iterations of the probabilistic relaxation process on the classification result. An optimal number of iterations then will be determined by experiments.

4 RESULT

The proposed method is tested using single look complex (SLC) fully polarimetric SAR data acquired over Penajam area, East Kalimantan Province. These data were acquired in L-band by Airborne E-SAR method on November 17th, 2004. The spatial resolution of the data used is 1.99 m and 3.0 m, in range and azimuth respectively. The scene under study contains different type of land covers: forest, fields, bare soils, and water area. Fig. 3 shows the RGB image (formed using Pauli decomposition) and a set of ground survey information.

For preprocessing, we construct scattering matrix from single look data (SLC) data for each polarization, then convert into polarimetric covariance matrix and coherency matrix, and apply speckle filtering using Lee Polarimetric Filter. In this experiment, a 3x3 window has been used. Larger windows provide more speckle smoothing but may smear fine details in the image. Totally, nine polarimetric parameters, i.e., three power / intensity (HH, HV, and VV), three polarimetric coherence, and three polarimetric phase difference are then extracted from polarimetric covariance matrix. Applying feature extraction based on Cloude’s polarimetric decomposition, three features i.e., entropy \( H \), mean alpha angle \( \alpha \), and anisotropy \( A \) are obtained. We then combine these two feature extraction results from both methods to form totally twelve features set and perform feature reduction using MNF transformation. Noise covariance is estimated using a homogeneous area in the images as shown in Fig. 3. The resulting bands of the MNF transformed data are shown in Fig. 4-a, with the associated eigenvalues are presented in Fig. 4-b. By analyzing eigenvalues and associated MNF bands, we can determine that most of the information contents are concentrated only on four first bands. In this case, eigenvalues are larger than 3. The remaining bands have
eigenvalues near one and the associated images are also predominantly by noise.

![MNF Bands](image)

![Log of Eigenvalue](image)

**b) MNF Eigenvalues**

Fig. 4. Results of maximum noise fraction (MNF) transformation for feature reduction purpose.

In order to better understand the behavior of the different feature extraction methods as well as the effectiveness of the feature reduction scheme based on MNF transformation, we carried out several trials generating four datasets as following:

1. A dataset with the nine features of polarimetric parameters
2. A dataset with the three features of Cloude’s polarimetric decomposition
3. A combined dataset of 1) and 2) (totally 12 features)
4. A dataset which contain reduced features after applying MNF transformation on dataset 3) (totally 4 features, i.e., four first MNF bands)

These four datasets are then employed as input for FMLE classifier. First, we carried out experiments without inclusion of spatial-contextual information. The classification results using dataset 1), dataset 2), dataset 3), and dataset 4) are shown in Fig. 5-a, 5-b, 5-c, and 5-d respectively. We can observe that polarimetric parameter features alone (see Fig. 5-a) can provide reasonable result, but with some misclassification between forest, fields, and bare soils. For example, the bare soil areas in upper left corners of the image were erroneously classified as forest. On the other hand, Cloude’s decomposition features (see Fig. 5-b) can identify accurately these bare soil areas and enhance the discrimination between forest and non-forest areas. By combining these two feature datasets, the discrimination of different land cover types can be improved, thus giving better classification result (see Fig. 5-c) than those obtained using datasets of each feature extraction methods. Fig. 5-d shows the classification result using reduced features dataset (MNF band 1-4). When the classification results in Fig. 5-c and 5-d are compared, it is clearly shown that although the dimension of the input features have been reduced (from 12 to 4 features), there is no significant deterioration in the classification result. Moreover, it is worth noting that the result obtained with reduced features dataset exhibit less “salt-and-pepper” effect than those obtained with the original (complete) dataset. These indicate that MNF transformation used in this study are not only effective for features reduction of our complete datasets but also useful for further speckle noise reduction.

Next, we apply probabilistic relaxation to these classification results to obtain spatial contextual information, and the results with 1, 3, 5, and 9 iterations are presented in Fig. 5-e, 5-f, 5-g, and 5-h respectively. To conserve the space, we only present the results of reduced features dataset (dataset 4)). Comparing with Fig. 5-d, although more homogeneous result is obtained, but the improvement is marginal. The classification results get more homogeneous (suppress more “salt and pepper” effect in homogeneous areas) by increasing the number of iteration. However, too many iterations lead to a widening of the effective neighborhood of a pixel to such an extent that fully irrelevant spatial information falsifies the final classification results. It can also be confirmed in Fig. 5-g and 5-h (with 5 and 9 iterations), which some erosion of the object boundaries (particularly when the objects are small in size) are occurred evidently. We conclude that the best results are obtained with 2-4 iterations, as it provide homogeneous classification result, but still preserve edge and other fine structures.

As comparison, the classification results using standard fuzzy K-means (FKM) clustering (using Euclidean distance) is also presented in Fig. 5-i. In all trials, we observed that the FMLE clustering perform consistently better than the FKM clustering. Some misclassification between forest, fields, water, and bare soils are occurred evidently, and particularly field class can not be accurately identified by FKM clustering algorithm.
A quantitative evaluation of the overall accuracy obtained in this proposed method was not possible, because a detailed ground truth of the analyzed region was not available. However, on the basis of the information available on some areas and of a careful visual inspection of RGB image (Fig. 3), we can conclude that the proposed approach provided satisfactory results.

Fig. 5. Classification results using FMLE clustering without and with spatial-contextual information based on probabilistic relaxation.
(Classification result using FKM clustering is also presented as comparison.)
5 CONCLUSION

An alternative method for unsupervised classification of polarimetric-SAR data has been proposed. The method was designed by integrating the combined features extracted from polarimetric covariance matrix and Cloude’s polarimetric decomposition (which characterize the target’s scattering mechanism) with spatial contextual-supported fuzzy maximum likelihood estimation (FMLE) classifier.

The proposed method has been tested on a fully polarimetric, single look complex E-SAR (L-Band) data acquired on the area of Penajam, East Kalimantan, Indonesia. Experimental results show that the proposed method improves land-cover discrimination performance, and provides robust and homogeneous classification results but still preserve edge and other fine structures.

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REFERENCE


