Subsurface Detection of Coral Reefs in Shallow Waters using Hyperspectral Data

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ABSTRACT

Hyperspectral Remote Sensing has the potential to be used as an effective coral monitoring system from either space or airborne sensors. The problems to be addressed in hyperspectral imagery of coastal waters are related to the medium, which presents high scattering and absorption, and the object to be detected. The object to be detected, in this case coral reefs or different types of ocean floor, has a weak signal as a consequence of its interaction with the medium. The retrieval of information about these targets requires the development of mathematical models and processing tools in the area of inversion, image reconstruction and detection. This paper presents the development of algorithms that does not use labeled samples to detect coral reefs under coastal shallow waters. Synthetic data was generated to simulate data gathered using a high resolution imaging spectrometer (hyperspectral) sensor. A semi-analytic model that simplifies the radiative transfer equation was used to quantify the interaction between the object of interest, the medium and the sensor. Tikhonov method of regularization was used as a starting point in order to arrive at an inverse formulation that incorporates *a priori* information about the target. This expression will be used in an inversion process on a pixel by pixel basis to estimate the ocean floor signal. The a priori information is in the form of previously measured spectral signatures of objects of interest, such as sand, corals, and sea grass.

Keywords: Remote Sensing, Pattern Recognition, Inverse Methods, Estimation Theory, Regularization, Hyperspectral Data, Image Reconstruction, Image Processing, Classification, Shallow Waters.

1. INTRODUCTION

A fundamental challenge to imaging systems and pattern recognition is the detection of objects embedded in a diffusive and dispersive medium with discrete sources of clutter. Particular examples of complex medium are the atmosphere, the ocean waters, and organic tissue. Most of the previous work has focused upon statistical detection and estimation of parameters. Physics-based modeling has been used to understand the relation between the objects of interest, the environment, and the sensors. The sensor mainly used is a high resolution imaging spectrometer (hyperspectral) sensor. Hyperspectral sensors provide measurements over hundreds of wavelengths of the electromagnetic spectrum. Data collected from such sensors have been widely used in remote sensing applications. This

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type of sensor has the capability to extract more detailed information with an increased accuracy. There are some fundamental challenges that need to be solved before being able to retrieve the potentially large amount of information from hyperspectral data. The applications will mainly focus on remote sensing to detect objects under the atmosphere or the ocean surface (e.g. coral reefs). An inverse problem arises as this spectral data is used to study an object underneath some medium. For our purposes the signal from the coral, or any other underwater target, is affected by the inherent absorption and scattering properties of water, along with absorption and scattering of chlorophyll, organic material and suspended sediment present in the medium.

The objective of this research is to apply inverse methods coupled with classification systems in order to improve the detection of objects embedded in highly complex medium.

2. RADIATIVE TRANSFER EQUATION

In remote sensing, the signal received at the airborne or spaceborne sensor has some distortion and attenuation due to the propagation through a complex medium. Radiative transfer equation (RTE) expresses in a mathematical formulation the interaction between the probe, the medium and the object of interest. The radiance received by a spaceborne or airborne instrument looking at nadir at an altitude of Z (km) is described by the RTE for plane parallel atmospheres as stated by Lenoble [1] is:

$$L_\lambda(Z) = \int_0^Z J_\lambda(s) \exp\left\{-\int_s^Z \sigma_{e\lambda}(s')ds'\right\} \sigma_{e\lambda} ds + L_\lambda(0) \exp\left\{-\int_0^Z \sigma_{e\lambda}(s)ds\right\} \tag{1}$$

where $J_\lambda(z)$ is a source function, which combines the medium emission, and energy scattered in the sensor field of view by the medium. $\sigma_{e_\lambda}(s)$ is the extinction coefficient defined as:

$$\sigma_{e\lambda} = \sigma_{\lambda_\alpha} + \sigma_{\lambda_\beta} \tag{2}$$

with $\sigma_{\lambda\alpha}$ being the absorption coefficient and $\sigma_{\lambda\beta}$ being the scattering coefficient. The boundary condition, $L_\lambda(0)$, includes components reflected and emitted by the surface. Due to its complexity, this representation presents problems when trying to solve for some parameters of interest, like the absorption and scattering coefficients, depth and albedo. A simpler formulation is needed in order to facilitate the development of an inverse model, necessary to estimate parameters that will be used to detect an object of interest.

A semi-analytical model based on the RTE was used to mathematically represent the propagation of the signal through the medium. The model used was proposed by Lee in [2,3]. In this model the signal received by the sensor is represented as:

$$r_{rs} = r_{rs}^{dp}\left(1 - \exp\left\{-\left[\frac{1}{\cos(\theta_w)} + D_u^C\right]kH\right\}\right) + \frac{1}{\pi}\rho \exp\left\{-\left[\frac{1}{\cos(\theta_w)} + D_u^B\right]kH\right\} \tag{3}$$

with,

$$r_{rs}^{dp} \approx (0.084 + 0.170u)u \qquad D_u^C \approx 1.03(1 + 2.4u)^{0.5} \qquad D_u^B \approx 1.04(1 + 5.4u)^{0.5}$$

and

$$u = \frac{\beta}{\alpha + \beta} \qquad k = \alpha + \beta$$

where r_{rs} is the subsurface remote sensing reflectance, θ_w is solar zenith angle, ρ is the bottom albedo, H is the bottom depth, α is the absorption coefficient and β is the backscattering coefficient. The last two parameters are wavelength dependent. The above-surface remote sensing reflectance (R_{rs}) is the signal received by the sensor. It is empirically related to the subsurface remote sensing reflectance by the following formulation:

$$R_{rs} \approx \frac{0.5 r_{rs}}{1 - 1.5 r_{rs}} \tag{4}$$

Thus, this model depends on the following variables H, θ_w, ρ, α and β. The bottom albedo (ρ) is the quantity we want to attain after the inversion process. The albedo is a property of the object, it is the fraction of radiation that it reflects. This information will be used for discrimination among objects once the inversion is done.

3. PROBLEM FORMULATION

3.1 Forward Model – Matrix Form

The semi-analytical model can be expressed in matrix form as follows:

$$\mathbf{b} = \mathbf{AP} = \begin{bmatrix} b(\lambda_1) \\ b(\lambda_2) \\ \vdots \\ b(\lambda_d) \end{bmatrix} = \begin{bmatrix} r_{rs}(\lambda_1) - S_{col}(\lambda_1) \\ r_{rs}(\lambda_2) - S_{col}(\lambda_2) \\ \vdots \\ r_{rs}(\lambda_d) - S_{col}(\lambda_d) \end{bmatrix} = \begin{bmatrix} a_{11} & 0 & \cdots & 0 \\ 0 & a_{22} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & a_{dd} \end{bmatrix} \begin{bmatrix} \rho(\lambda_1) \\ \rho(\lambda_2) \\ \vdots \\ \rho(\lambda_d) \end{bmatrix} \tag{5}$$

where $a_{ii} = \frac{1}{\pi} \exp\left\{ -\left[\frac{1}{\cos(\theta_w)} + D_u{}^B \right] kH \right\}$ meanwhile $S_{col} = r_{rs}{}^{dp} \left(1 - \exp\left\{ -\left[\frac{1}{\cos(\theta_w)} + D_u{}^C \right] kH \right\} \right)$ is the water column contribution at λ_i wavelength. Our goal is to develop a suitable inverse formulation of the forward model presented before. This formulation should be such that permits the estimation of $\rho(\lambda_i)$, accounting for the uncertainties present in the observations and measurements. This quantity will be used to detect our object of interest.

3.2 Inverse Model

We considered three possible formulations of the inverse model. The first one simplify the formulation by assuming $\mathbf{A} = \mathbf{I}$ and that $\mathbf{S_{col}(\lambda_i)} = 0$, as a consequence **b=P.** This expression does not consider the absorption and scattering of the medium. The water column contribution is also neglected.

The inverse model can be stated in a second formulation as $\mathbf{P} = \arg\min\left\{ \|\mathbf{AP} - \mathbf{b}\|_2^2 \right\}$, where **P** is the least square solution. This formulation is often used when the problem is overdetermined, meaning that $\mathbf{A} \in \Re^{mxn}$ with $m > n$. In the particular case we are discussing $m = n$, as a consequence the least square problem can be stated as $\mathbf{P} = \mathbf{A}^{-1}\mathbf{b}$. Yet, this formulation does not account for the uncertainties present in the problem. These uncertainties are present in the measurements or estimations of the following variables: H, θ_w α and β.. These uncertainties, present in the matrix $\boldsymbol{A}$ and vector $\boldsymbol{b}$, have to be accounted for.

In a third formulation regularization can be used to address this difficulty. The purpose is to estimate the response of the target (ρ) under conditions of imprecise measurements or knowledge of the parameters and the uncertainties of the forward model. Tikhonov regularization will be used to accomplish this objective. The key aspect of this method is the incorporation of *a priori* information about the desired solution in the inversion process. This *a priori* information is used to deal with the uncertainty present in the measurements, in order to stabilize the problem and obtain a useful result. The inverse problem solution using Tikhonov regularization can be expressed as:

$$\mathbf{P}_{reg} = \arg\min\left\{\left\|\mathbf{AP}-\mathbf{b}\right\|_2^2 + \eta^2\left\|\mathbf{P}-\mathbf{P}_0\right\|_2^2\right\} \quad (6)$$

or in matrix form as:

$$\mathbf{P}_{reg} = (\mathbf{A}^{\mathbf{T}}\mathbf{A}+\eta^2\mathbf{I})^{-1}(\mathbf{A}^{\mathbf{T}}\mathbf{b}+\eta^2\mathbf{P}_0) \quad (7)$$

$\mathbf{P}_0$ represents the *a priori* stored spectral signature of objects of interest (spectral signatures of coral reefs, pollution plume, sand, grass, etc.). $\boldsymbol{P_0}$ is an *a priori* estimate of the solution. For computational purposes β^2 has been expressed as:

$$\eta^2 = \frac{\gamma}{1-\gamma} \quad (8)$$

where $\gamma \in [0,1)$. This parameter, γ, functions as a regularization parameter. Since in this case the matrix **A** is a diagonal matrix, Equation 7 can be reformulated as:

$$P_{reg}(\lambda_i) = \frac{a_{ii}^2}{a_{ii}^2+\eta^2}\frac{r_{rs}(\lambda_i)-S_{col}(\lambda_i)}{a_{ii}} + \frac{\eta^2}{a_{ii}^2+\eta^2}P_0(\lambda_i) \quad (9)$$

or

$$P_{reg}(\lambda_i) = k_0 P(\lambda_i) + k_1 P_0(\lambda_i) \quad (10)$$

Because $k_0 + k_1 = 1$, the solution $P_{reg}(\lambda_i)$ can be seen as a convex combination of $P(\lambda_i)$, the least square solution formulated previously, and $P_0(\lambda_i)$ which is the *a priori* information. As γ tends to one, the solution $P_{reg}(\lambda_i)$ is forced to be closer to the stored signature $P_0(\lambda_i)$. If γ is too small, the is the least square solution, $P(\lambda_i)$, will prevail. In the last case there is a risk that the signature of the target remains obscured in the medium due to uncertainties. It is important to select a regularization parameter γ that enables discrimination between the object and the surrounding clutter.

4. SELECTION OF THE REGULARIZATION PARAMETER

The first step is to select the regularization parameter, γ. The considered approach treats each pixel as an independent inverse problem. Each pixel will be inverted using a distinctive regularization parameter, γ, and incorporating *a priori* information in terms of a store spectral signature, $\mathbf{P}_0$. This approach does not require the use of labeled samples.

5.1 Selecting the regularization parameter on a pixel by pixel basis: *a priori* information in terms of stored spectral signatures

Since selecting the regularization parameter is done pixel by pixel in this approach there are no labeled samples to estimate parameters. The *a priori* information here is in the form of stored spectral measurements. Two things have to be determined, the value of the regularization parameter and what spectral signature to use as *a priori* information in the form of $\mathbf{P}_0$. The R_{rs} represented in each pixel is inverted using as *a priori* information every spectral signature $\mathbf{P}_{0i}$ in the spectral library. The regularization parameter γ will be selected so that it minimizes a measure of error between $\mathbf{P}_{reg}$ and $\mathbf{P}_0$ for each signature in the library. Let $E_i(\gamma)$ be defined as:

$$E_i(\gamma) = \left\| \mathbf{P}_{reg} - \mathbf{P}_{0i} \right\|_2^2 \qquad (11)$$

$\mathbf{P}_{reg}$ is obtained according to Equation 7. Observe that as γ tends to one $\mathbf{P}_{reg}$ tends to $\mathbf{P}_0$. As a consequence $E_i(\gamma)$ decrease as a function of γ for every spectral signature $\mathbf{P}_{0i}$. Our objective is to find the spectral signature that reduces $E_i(\gamma)$ faster. Also it is of our interest to find a small enough value of the regularization parameter, γ, that also produces a small error, defined by Equation 11. This value of γ will be selected as the value that lies in the "elbow" or "corner" of the function $E_i(\gamma)$, as shown in Figure 1. This will be selected as the point of maximum curvature of the error function $E_i(\gamma)$, defined as:

$$\gamma_i = \arg\max \left\{ \frac{E_i(\gamma_i)''}{\left(1 + E_i(\gamma_i)'\right)^{\frac{3}{2}}} \right\} \qquad (12)$$

This is similar to the L-Curve criterion for selection of the regularization parameter stated by Hansen [4,5]. The steps in this procedure as summarized as follows:

For every pixel in the image:

1. Formulate the estimation of the spectral content $\mathbf{P}_{reg}$ according to equation (7) using all available stored spectral signatures $\mathbf{P}_{0i}$.
2. Compute the error $E_i(\gamma_i)$ for every stored spectral signature.
3. Find the γ_i in every $E_i(\gamma)$ as defined in Equation 12.
4. The regularization parameter to be used, γ_{opt}, is the one that accomplish the following rule accomplish:

$$\gamma_{\text{opt}} = \min(\gamma_i), \quad \forall i \qquad (13)$$

The selected spectral signatures $\mathbf{P}_{0i}$ is the one that is connected to γ_{opt}.

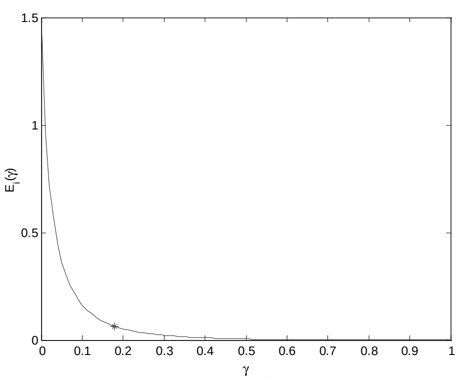

Figure 1: Selection of the regularization parameter for one class.

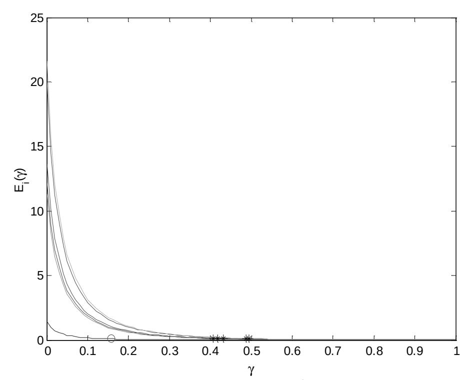

Figure 2: E(γ) computed for each $\mathbf{P}_{0i}$. γ_{opt} (circled) is the minimum of all the selected γ_i.

Figure 2 shows the graph of the different $E_i(\gamma)$ with respect to γ. Decision of what signature to use as *a priori* information will be based on which signature generates the smallest γ, thus requiring less regularization in the inversion process. In the case that various γ are the same, the one that yields the smallest error will be selected. Inversion will then proceed with the calculated regularization parameter γ_{opt} and with the selected spectral signature as *a priori* information.

5. EXPERIMENTS AND RESULTS

5.1 Experiments with Selecting the Regularization Parameter on a pixel by pixel basis: Synthetic Data

Experiments were conducted using synthetic data generated with Hydrolight v.4.2 [6]. The data was generated using the spectral responses of several targets, at a wavelength range from 400nm to 700nm in steps of 10nm, and adding the effects and Case 2 waters. Six targets were used: Coral (Acropora), Coral Sand, Clean Seagrass, Brown Algae, Green Algae and Red Algae. The dry spectrums of these make up a spectral library, which will be used as *a priori* information. Remote sensing reflectance, R_{rs} , obtained by the simulations were used as the signal received by the sensor. It will be assumed that the bottom depth and the solar zenith angle are known, a bottom depth of 2m with a solar zenith angle of 0^o from nadir. Also it will be assumed that there is some knowledge (historical data, measurements) about the absorption and backscattering coefficient of the area studied in the image. In this case, absorption and backscattering coefficients obtained from the simulation were used as probable *in situ* measurements.

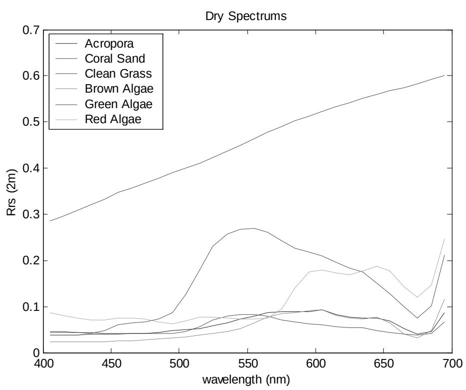

Figure 3: Dry spectrum of the targets

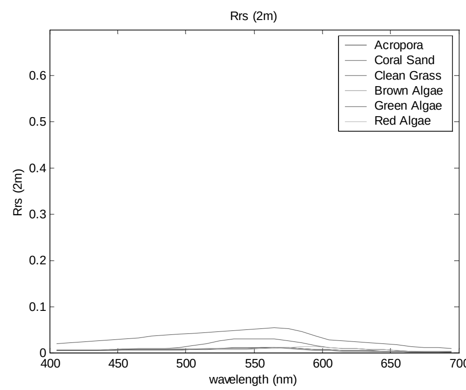

Figure 4: Spectrum of the targets, 2m Case 2 waters

Images were constructed using the simulated data and consist of four regions, each one representing one class. Zero mean Gaussian noise with a standard deviation of .001 was added to create variability in every pixel. The images were reconstructed by considering each pixel as an inverse problem. Classification was done after the inversion process, by means of Euclidean Distance Classifier. An inverted pixel, $\mathbf{P}_{reg}$, will be classified as belonging to class *i* if the following rule is satisfied:

$$\min_i \left(\mathbf{P}_{reg} - \mathbf{P}_{0i}\right)^T \left(\mathbf{P}_{reg} - \mathbf{P}_{0i}\right) \qquad (14)$$

where each class *i* is defined by a stored spectrum of the object without the effect of the medium. Thus, a pixel will be classified as class *i* if it yields the minimum Euclidean Distance when compared with the spectrum $\mathbf{P}_{0i}$.

5.2.1 Classification without inversion: $\mathbf{A} \approx \mathbf{I}$, $\mathbf{S}_{col}(\lambda_i) = 0$.

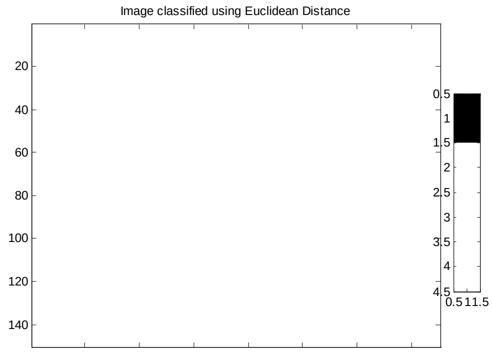

Figure 5

Classification Accuracy	
Coral (Acropora)	0%
Clean Grass	100%
Red Algae	0%
Brown Algae	0%
Total	26.4089%

Table 1

5.2.2 Classification with inversion: $\mathbf{P} = \mathbf{A}^{-1}\mathbf{b}$.

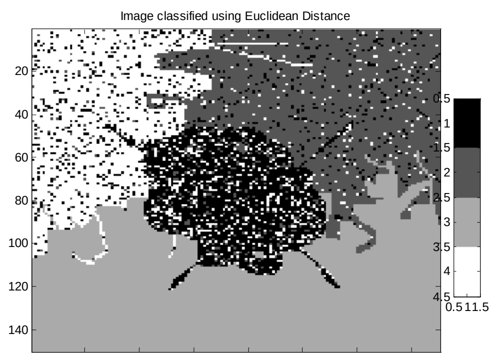

Figure 6

Classification Accuracy	
Coral (Acropora)	73.9754%
Clean Grass	89.9865%
Red Algae	100%
Brown Algae	86.4300%
Total	90.5511%

Table 2

Figure 5 shows the results under the conditions that it is assumed that $\mathbf{A} \approx \mathbf{I}$ and $\mathbf{S}_{col}(\lambda_i) = \mathbf{0}$. We can see in Table 1 a classification accuracy of about 26 %. Because of the lack of medium information all the pixels were classified as belonging to only one class. When using $\mathbf{P} = \mathbf{A}^{-1}\mathbf{b}$ (Figure 6) there is a significant increase in accuracy as the medium information is incorporated in the inversion process as shown in Table 2.

5.2.3 Classification with inversion using regularization: $P_{reg} = \arg\min\left\{\|\mathbf{AP} - \mathbf{b}\|_2^2 + \eta^2\|\mathbf{P} - \mathbf{P}_0\|_2^2\right\}$

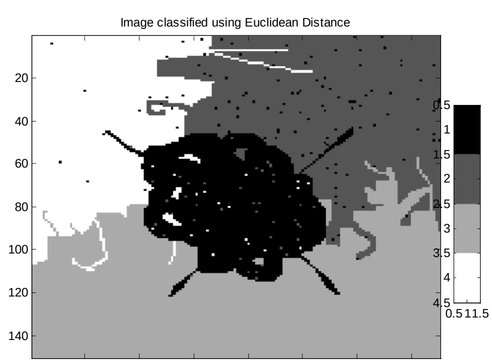

Figure 7

Classification Accuracy	
Coral (Acropora)	98.3663%
Clean Grass	98.3676%
Red Algae	100%
Brown Algae	99.6515%
Total	99.2444%

Table 3

Figure 7 shows the results using the formulation expressed by equation 7. The total detection accuracy is increased from 90% to 99% when compared with the results obtained by using $\mathbf{P} = \mathbf{A}^{-1}\mathbf{b}$.

6. CONCLUSION

The main purpose of this research was to develop a method to accomplish the retrieval of information from an object beneath some medium with high scattering and absorption properties. This was achieved using data that simulates information obtained from a high resolution imaging spectrometer (hyperspectral) sensor in the visible area of the electromagnetic spectrum. Our interest was the detection and classification of targets (i.e. coral reefs, sand, seagrass, etc.) under water. This medium possesses inherent absorption and scattering properties. A semianalytic forward model was used to account for the interaction of the signal through this medium. This model enables the development of an inverse model. The model described in equation (3) depends only on H, θ_w, ρ, α and β, and enables the estimation of $\rho(\lambda_i)$, which is the variable of interest. H, θ_w, α, and β can be measured or estimated and posses uncertainties that arise in the process of data analysis.

Once the problem was expressed in matrix form three formulations of the inverse model were considered. The first one assumed that $\mathbf{A} = \mathbf{I}$ and that $\mathbf{S_{col}(\lambda_i)} = 0$, leaving the problem to be expressed as $\mathbf{b} = \mathbf{P}$. This particular formulation did not take into consideration information about the medium. The second formulation is related with the least squares solution $\mathbf{P} = \arg\min\left\{\|\mathbf{AP} - \mathbf{b}\|_2^2\right\}$. Information could be extracted, as medium characterization was present, yet the uncertainties from the measurements or estimation of H, θ_w, α and β were not accounted for. In the third formulation, using Tikhonov regularization, the medium characterization and *a priori* information were incorporated. An unsupervised approach was developed in order to incorporate *a priori* information, to account for uncertainties, and selection of the regularization parameter γ. The albedo was estimated according to the following rule $\mathbf{P}_{reg} = \arg\min\left\{\|\mathbf{AP} - \mathbf{b}\|_2^2 + \eta^2\|\mathbf{P} - \mathbf{P}_0\|_2^2\right\}$ with $\eta^2 = \dfrac{\gamma}{1-\gamma}$, and $\gamma \in [0,1)$ being the regularization parameter to be calculated. The regularization parameter, γ, was chosen so that it would be a small enough value while producing a small error. Due to these additional characteristics in the formulation, the classification accuracy was enhanced and more information could be extracted from the data.

7. ACKNOWLEDGEMENTS

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