Classification of sonar measures using optimized wavelets

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Abstract- This paper presents methods to extract features from received echoes from a sonar. Once the features are extracted, performances are estimated using a Linear Discriminant Analysis to classify the sea bottom in 2 classes, sand and posidonia.

I. INTRODUCTION

In order to be able to navigate, an autonomous underwater vehicle needs to perceive its environment. One possible approach is to follow natural features such as borders of posidonia patches. To follow the boundary between distinct benthic regions, exteroceptive sensors like cameras or sonars, together with pattern recognition methods must be used. In this work, we use the ROV phantom (see figure 1) equipped of a sonar (Tritech Seaking Profiler) and a video camera.

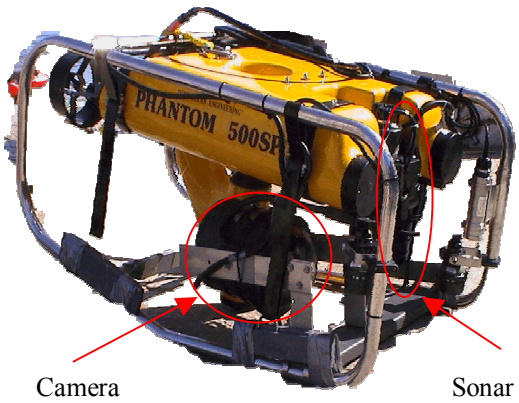

Figure 1: The ROV phantom

In the past, we implemented algorithms for tracking contours of posidonia patches using vision. In this paper, we improve tracking robustness by using sonar measurements. The sonar is oriented toward the sea bottom while the camera observes the same region, providing ground truth information about the distinct sea bottom type. In this experiment only two classes are present: posidonia and sand. The objective is to class scanned sea bottom into the corresponding class, it's a pattern recognition problem.

To estimate the parameters of the classifier and test his performances we construct 2 sets of measurement, one for learning and the other for validation.

The results of the pattern recognition depend strongly on the vector of features extracted from the raw data. Our work proposes to use decomposition on wavelet packet best basis [1] as a feature extractor and optimised wavelet [2] to improve the results for small feature dimensions. The aim is to construct an adaptive orthonormal basis which is localized in the time-frequency plane and which discriminates the two signal classes. In [1] The choice of the mother wavelet is fixed a priori. We follow the approach proposed in [2], optimizing the mother wavelet to adapt it to the signal to be discriminated. Once the expansion coefficients of the signal in this basis are computed, we want to reduce the dimension of the feature vector. The method used is Sequential Backward Selection, [3]. Results using the wavelet packet expansion coefficients are presented and compared to features extracted with PCA method. We use classical method to classify the measures: Linear Discriminant Analysis. The performances is estimated on a new set of measures not used in the estimation process of the Best Local Basis and of the classifier parameters.

Finally, we show real experiment on the extraction of the border between sand and posidonia based on the classifier results.

II. THE LEARNING SET

A The sensor

The sensor used to scan the sea bed is a Tritech Seaking profiler Sonar. During our experimentation, the following configuration has been used :

The sonar is oriented toward the sea bottom and scans between +30° to –30°, is mounted in the front of the ROV (see Figure 1).

Depth resolution: ± 0.02 m.

Frequency of the emitted signal: 1.2 MHz.

Beamwidth: 1.4° Conical

Mechanical step size: 0.9°

B The features

The sea bottom observed at Villefranche-sur-mer presents of only two classes: posidonia and sand. To perform pattern recognition, features must be extracted from the raw data. Preprocessing extracts the 32 measures around the maximum (see Figure 2) which represents the interesting information returned from the sea bottom. Two methods are presented and compared to extract the features from the preprocessed samples (basic features):

- Principal Component Analysis
- Wavelet packet decomposition [4].

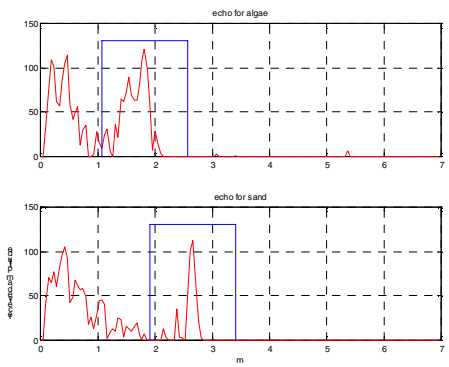

Figure 2: Received echo for the 2 classes

1) Principal Components Analysis

The main objective of the PCA method consist of expressing the information by a lower number of variables called the principal components. These principal components are linear combinations of the original variables.

The PCA method gives statically and geometrically orthogonal variables. The corresponding eigenvalue express the data variance of the new variable. This approach is used to reduce the dimension of the problem. For each dimension the classification performance is estimated and we select the dimension which gives the best results.

2) Wavelet packets decomposition on best basis

The wavelet packet is a generalization of the wavelet decomposition [5]. In the wavelets packet we decompose the approximation coefficient vector and the detail coefficient vector. The decomposition can be represented by a binary tree (see figure 3). The wavelets are defined from the scaling function $\phi(t)$ by:

$$\psi_{j+1}^{2p}(t) = \sum_{n=-\infty}^{+\infty} h[n]\psi_j^p\left(t-2^j n\right) \tag{1}$$

$$\psi_{j+1}^{2p+1}(t) = \sum_{n=-\infty}^{+\infty} g[n]\psi_j^p\left(t-2^j n\right) \tag{2}$$

$$\psi_0^0(t) = \phi(t) \tag{3}$$

j defining the resolution level and p the analyzed frequency band.

The filter h is related to the scaling function ϕ and g is related to the mother wavelet ψ:

$$\phi(t/2) = \sqrt{2}\sum_n h[n]\phi(t-n) \tag{4}$$

$$\psi(t/2) = \sqrt{2}\sum_n g[n]\phi(t-n) \tag{5}$$

$$g(n) = (-1)^{1-n} h[1-n] \tag{6}$$

We denote:

$$d_n^p[n] = \left\langle f(t), \psi_j^p\left(t-2^j n\right)\right\rangle \tag{7}$$

For each node (j,p) of the binary tree the coefficients of wavelet packets:

The coefficient of wavelet packets of the decomposed signal x are given by:

$$\begin{aligned} d_{j+1}^{2p}[k] &= d_j^p * \bar{h}[2k] \\ d_{j+1}^{2p+1}[k] &= d_j^p * \bar{g}[2k] \\ d_0^0[k] &= x[k] \\ \text{with } \bar{f}[n] &= \bar{f}[-n] \end{aligned} \tag{8}$$

The decomposition is represented on the following figure. The ↓2 represents downsampling (we keep the even indexed elements).

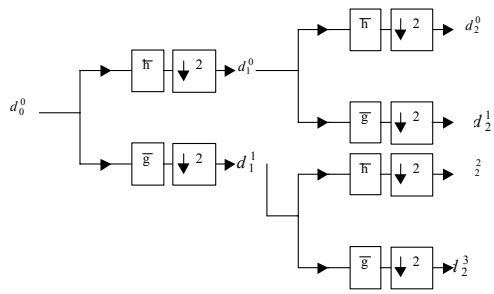

Figure 3: Binary tree

According to [1] we construct an orthonormal basis which maximizes class separability for signal classification problems. Once the discrete signal is decomposed on the best basis BP^h (*h* represents the filter h used to decompose the signal) we select the most discriminating features (wavelet packets coefficients). This feature selection is presented in section 3.

The mother wavelet is related to the filter *h* by the equations (5) and (6). The classification is based on the wavelet packets coefficients and is related to the filter *h*. In [2] the authors propose to select *h* (and the related mother wavelet) which yields the best classification results.

The parametric filter shape is defined by

$$\begin{aligned} & i = 0,1 \\ & h[i] = \frac{1}{(4.\sqrt{2})}\begin{bmatrix} \left(1+(-1)^i.\cos(a)+\sin(a)\right) \\ \left(1-(-1)^i\cos(b)-\sin(b)\right) \\ +(-1)^i.2.\sin(b)\cos(a) \end{bmatrix} \\ & i = 2,3 \\ & h[i] = [(1+\cos(a-b)+(-1)^i.\sin(a-b))]/(2.\sqrt{2}) \\ & i = 4,5 \\ & h[i] = (1/\sqrt{2}) - h(i-4) - h(i-2) \end{aligned} \tag{9}$$

We have 2 independent parameters $(a,b) \in [-\pi,\pi]^2$.

The parametric filter must satisfy the following structural constraints

$$\begin{aligned} & \sum_{n=1}^{M} h[n] = \sqrt{2} \\ & \sum_{n=1}^{M} h^2[n] = 1 \\ & \sum_{n=1}^{M} h[n].h[n-2k] = 0 \text{ for k} = 1,..,\text{M/2 -1} \end{aligned} \tag{10}$$

The method follow the steps

1. Select *a* and *b*.
2. Compute *h(a,b)*.
3. Decompose the signal from the learning set on the wavelet packets basis related to *h(a,b)*.
4. Compute the best basis BP^h.
5. Reduce the dimension of the feature vector.
6. Evaluate performance on the validation set.

C Dimension reduction

We can use feature selection methods to reduce the size of the classification pattern without or with little performance degradation. A dimensionality reduction can even improve the generalisation results because fewer parameters must be estimated during the learning process. The method searches the subspace where the classes are well separated. The criterion generally used to express the separability of the classes in a particular subspace [3] is:

$$J = trace\left(\hat{\Sigma}_W^{-1}.\hat{\Sigma}_B\right) \tag{11}$$

where:

$\hat{\Sigma}_W$ is the estimated intra group covariance matrix and

$\hat{\Sigma}_B$ is the estimated inter group covariance matrix

Two kinds of methods are proposed to achieve the selection: Optimal and Sub-optimal. The first needs more computation. Only the second is presented and used due to the high dimension of the problem (32 features).

'Sequential Backward Selection' (SBS): We begin with the whole set of features and remove the irrevelant attributes one by one. At the kth step, we remove the feature ξ_j as:

$$J(\Xi_k / \{\xi_j\}) \geq J(\Xi_k / \{\xi_i\}) \quad i = 1, d-k \quad \text{i} \neq \text{j} \tag{12}$$

where *J* is the criteria (equation 11), Ξ_k is the whole set of features minus *k* features.

III. PATTERN RECOGNITION METHODS

A *p* dimensional feature vector is denoted by $x = [x_1,..,x_p]^T \in R^p$ and its associated class by $k \in \{1,..,K\}$. A classifier can be regarded as a mapping $c : R^p \to \{1,..,K\}$ that associates a given feature vector *x* to the class $c(k)$.

For 2 classes the optimal Bayes rule $c(x)$ which minimizes the expected error rate with equals prior probability for the 2 classes is :

$$c(x) = \begin{cases} 1 \text{ if } \Lambda(x) > 1 \\ 2 \text{ if } \Lambda(x) < 1 \end{cases} \tag{13}$$

with:

$$\Lambda(x) = \frac{f_1(x)}{f_2(x)} \tag{14}$$

Where $f_k(x)$ is the density probability of class k, and $\Lambda(x)$ is the likelihood ratio.

In the following we assume that pattern vectors from class k are normally distributed with mean vector μ_k and covariance matrix Σ_k .

If we assume that the classes are normally distributed with different mean vectors but with common covariance matrix Σ, the decision rule is the LDA rule.

The maximal likelihood parameters of the classes are estimated using the training data.

IV. PERFORMANCES

This section compares the performances on the methods discussed before using real data.

To create the leaning and the validation sets with known classes, we use the video camera to match the sonar measure with the corresponding classes.

The data set is divided in two sets, one learning set and a validation composed of 1850 samples of the two classes. SBS (see section II.C) is used to select the most discriminative features.

The good classification percentage for the two classes are presented depend on the feature dimension on the validation set.

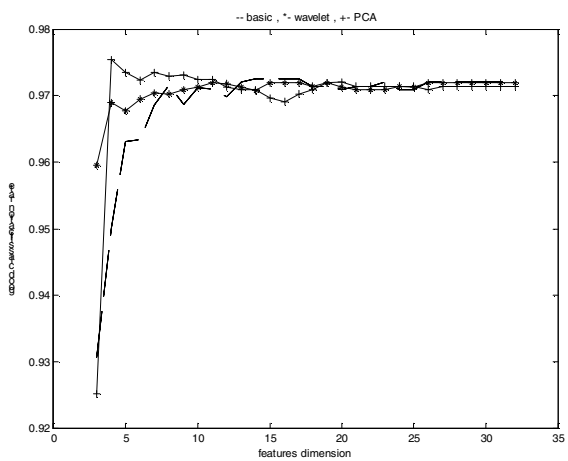

Figure 4: Classification performances for the 3 approaches, wavelets packets coefficients, PCA coefficients and basic features.

Discussion:

The Figure 4 shows the performance obtained with the three approaches:

- PCA coefficients: The best result is obtained for the dimension 4 (69.4% of the total variance for the 4 principal components).
- Wavelets packets coefficients: The best result is obtained for the dimension 3 (with the parameters a = 0.8 and b = 0.8).
- Basic features: The features are composed only by the preprocessed data (see II.B).

The best result is obtained with the PCA for feature dimension 4 (see Table), but if we want to reduce the dimension the best results are obtained with the wavelet packet coefficients with 3 features (see Table II). And in any cases, the initial features set gives lowers results.

TABLE 1: CLASSIFICATION RESULTS FOR FEATURE DIMENSION 4.

method		class sand	class posidonia
Wavelets packets	class sand	99.7%	7.8 %
4 features	class posidonia	0.3 %	92.2%
PCA	class sand	99.8%	5 %
4 features	class posidonia	0.2 %	95 %
Basic	class sand	97.9 %	7.9 %
4 features	class posidonia	2.1 %	92.1%

Table II: Classification results for feature dimension 3.

method		class sand	class posidonia
Wavelets packets	class sand	99.7 %	7.8 %
	class posidonia	0.3 %	92.2 %
PCA	class sand	97.3%	12.3 %
	class posidonia	3.7 %	87.7 %
Initial	class sand	97.2 %	11.1 %
	class posidonia	3.8 %	88.9 %

The objective of the method is to detect the border of posidonia and sand, the following experimentation will show the correct detection the of borders between the two classes.

The experimentation is effected with the same previous configuration. During the moving of the ROV sonar scan and video images (2 images/sec) are recorded. We cross posidonia and sand sections. Off line, a mosaic of video image is created using correlation method. The sonar scans are classified using the previous classifier with 4 PCA features. The sonar scans too close from the sea bottom are not classified (inferior to a minimal distance of 0.4m) because there are corrupted by the crash frame of the ROV. Using the identified geometrical model from the scan reference frame to the image reference frame, we can superimposed the classified scan onto the mosaic images. The classification results are estimated by comparing the ground true represented by the mosaic of images and the classified scans.

We can see on figures 5-12 in annexes the correct detection of border between the 2 classes. For fourteen transitions existing, twelve are correctly detected, one is not detected (Figure 9) and one wrong detection (Figure 9).

V. CONCLUSION

This paper presents methods to classify sea bottom composed of posidonia and sand. Different approaches are compared and evaluated. The best classification results are obtained with the PCA method and LDA classification. The dimension is reduced to 4 features compare to the 32 initial features. But for a more reduced dimension wavelet packet decomposition on best basis presents the best results (for dimension 3).To show the performances the classified scans are superimposed onto a mosaic image of the seabed and the correct detection of transition between the 2 classes are estimated (12/14). The future work is to develop a adaptive non supervised method to classify the sea bottom. Because, the approach presented here is only valid if the classes are known.

ACKNOWLEDGEMENTS

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ANNEXES

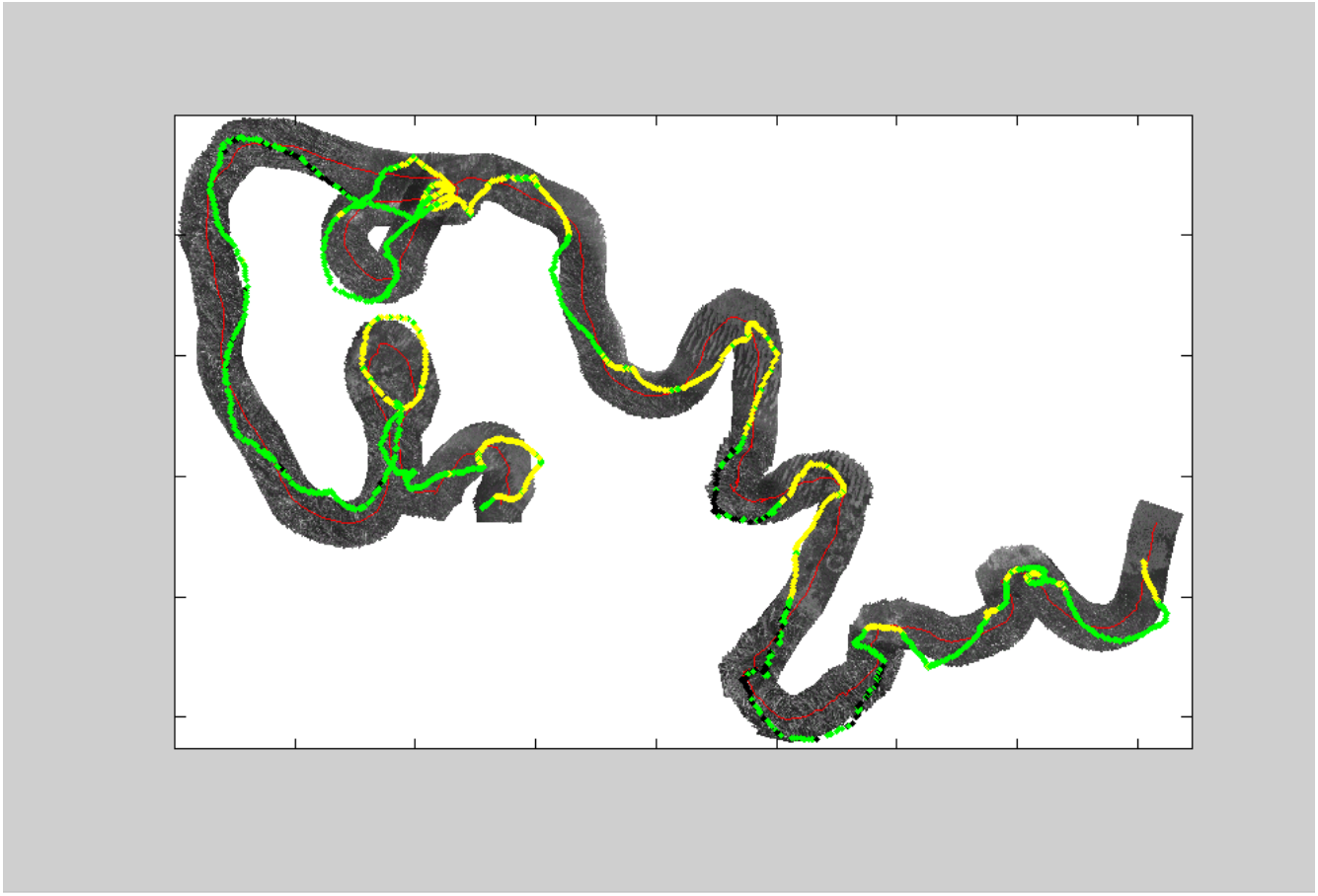

Figure 5: The classified scan superimposed onto the video mosaic. In green the posidonia class, in yellow the sand class, in red the center of the images.

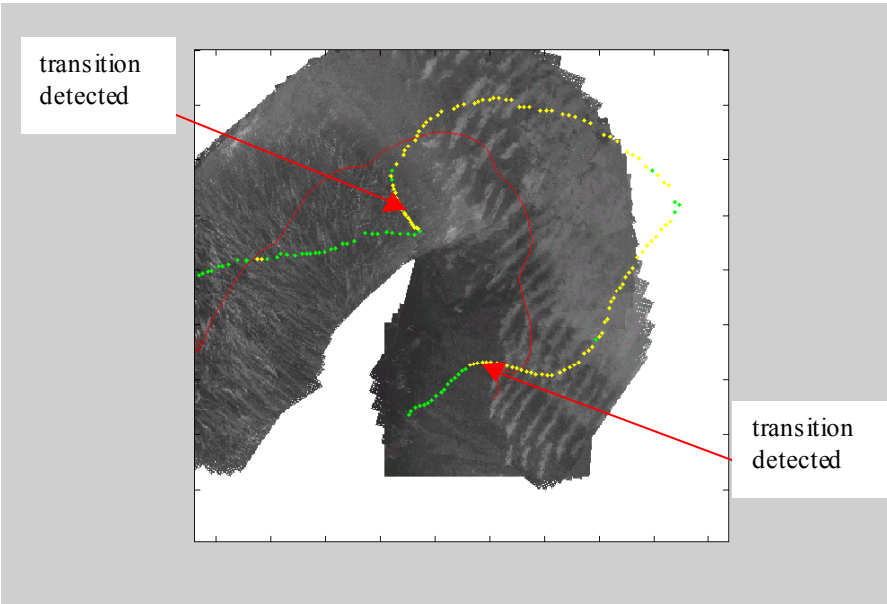

Figure 6: Two transitions correctly detected

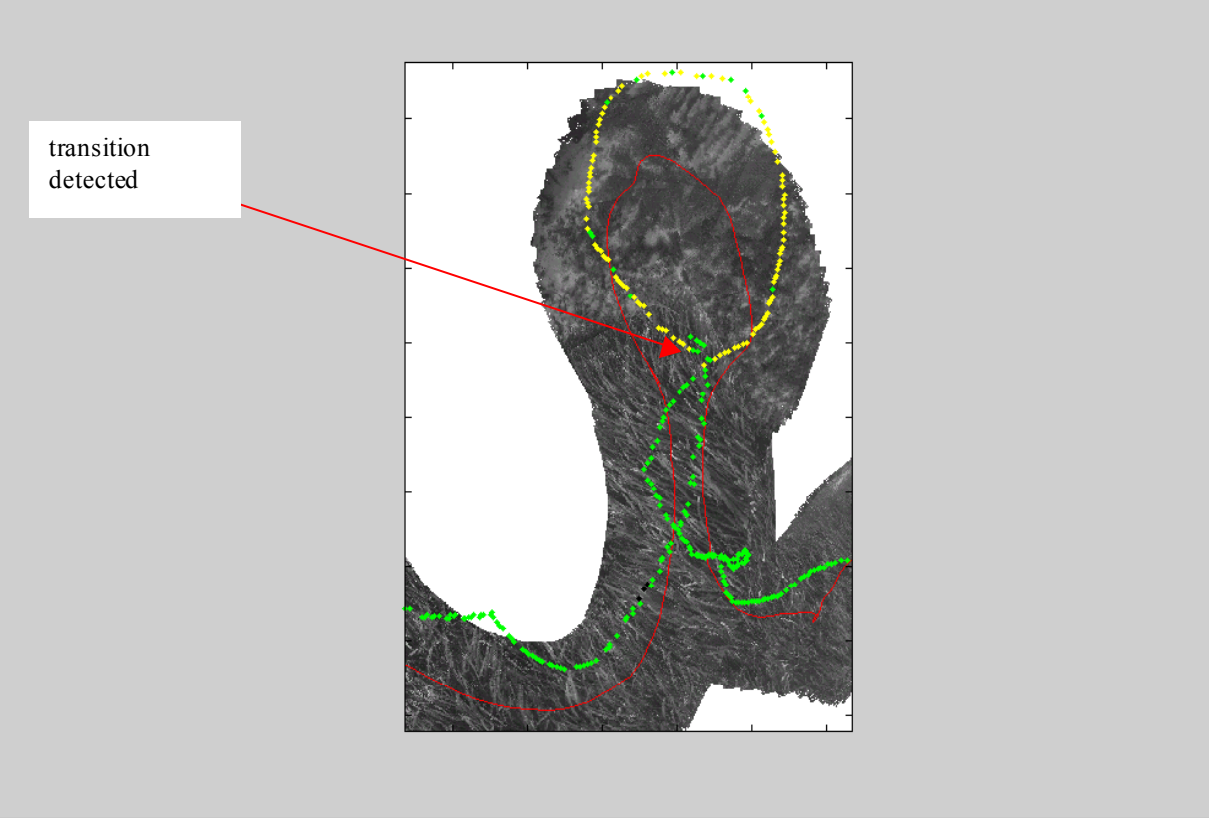

Figure 7: One transition correctly detected.

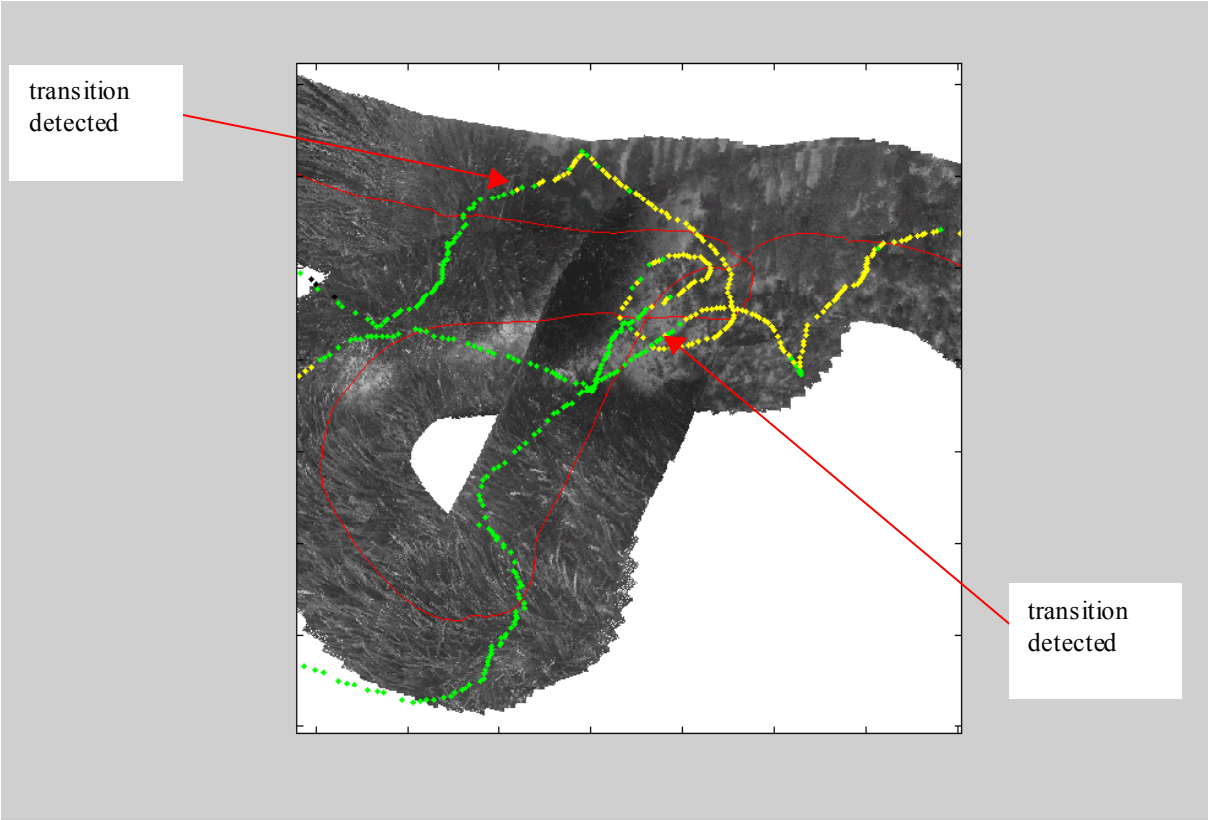

Figure 8: Two transitions correctly detected.

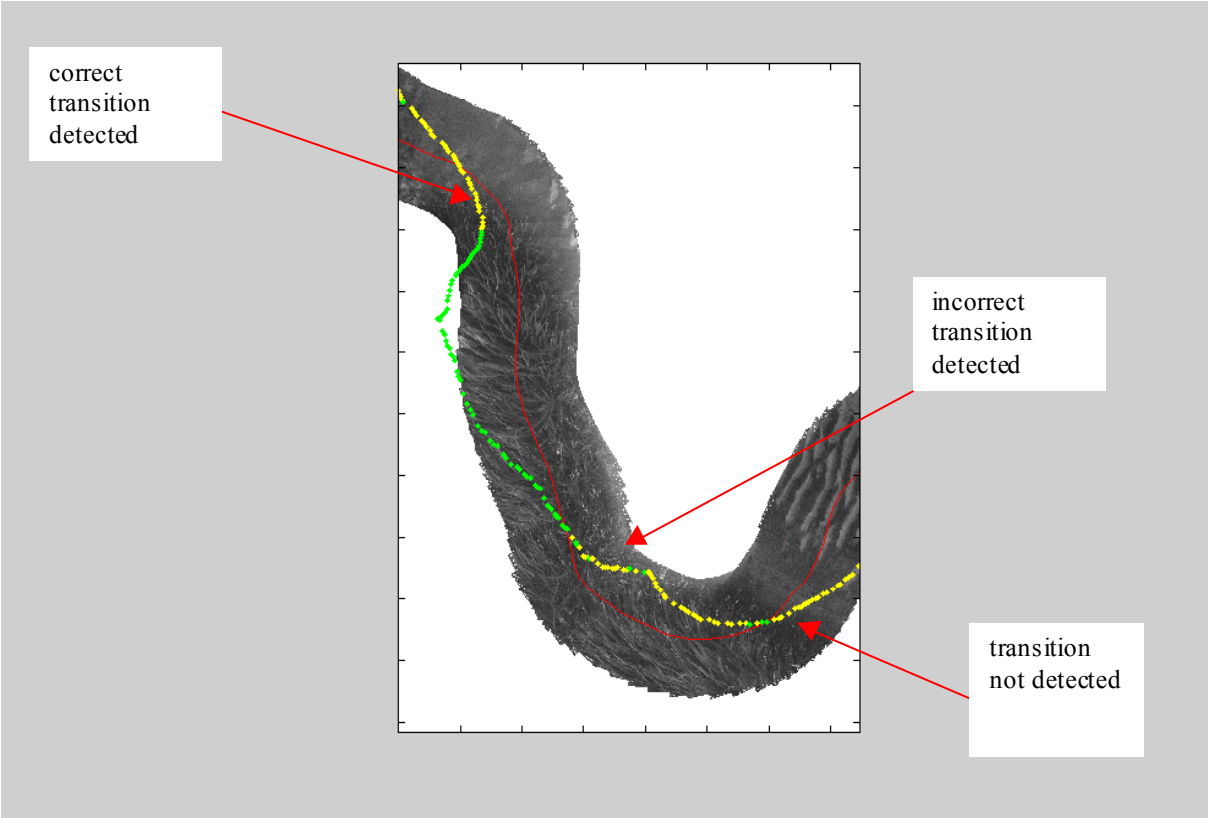

Figure 9: One transition correctly detected, one incorrectly detected and one none detected.

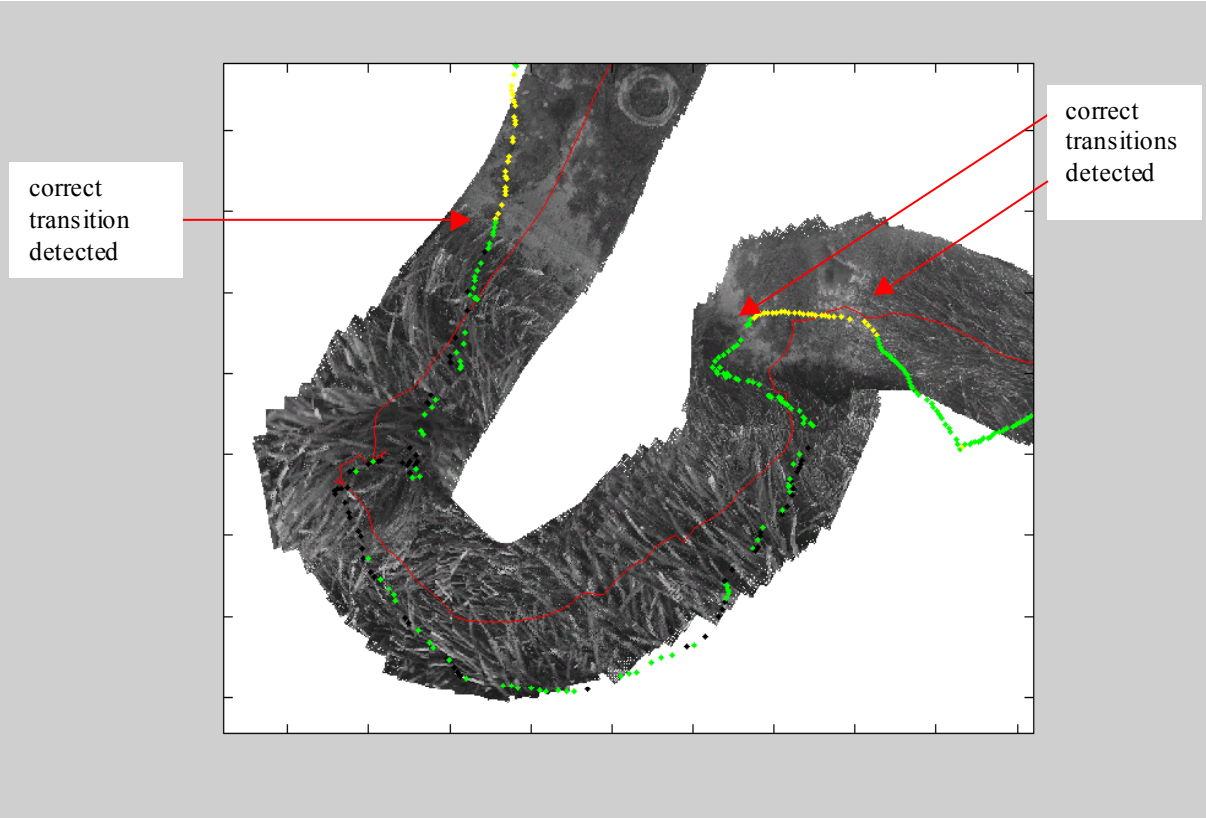

Figure 10: Three transitions correctly detected.

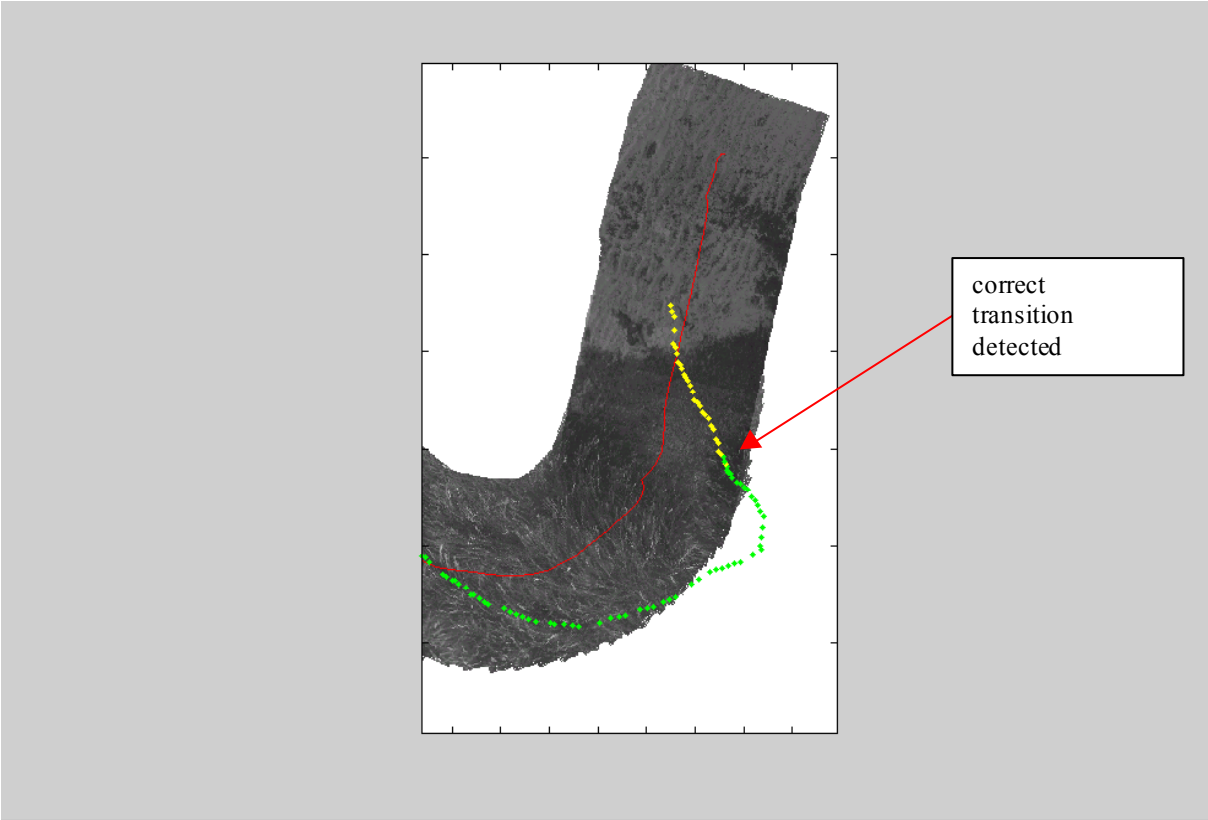

Figure 11: One transition correctly detected.

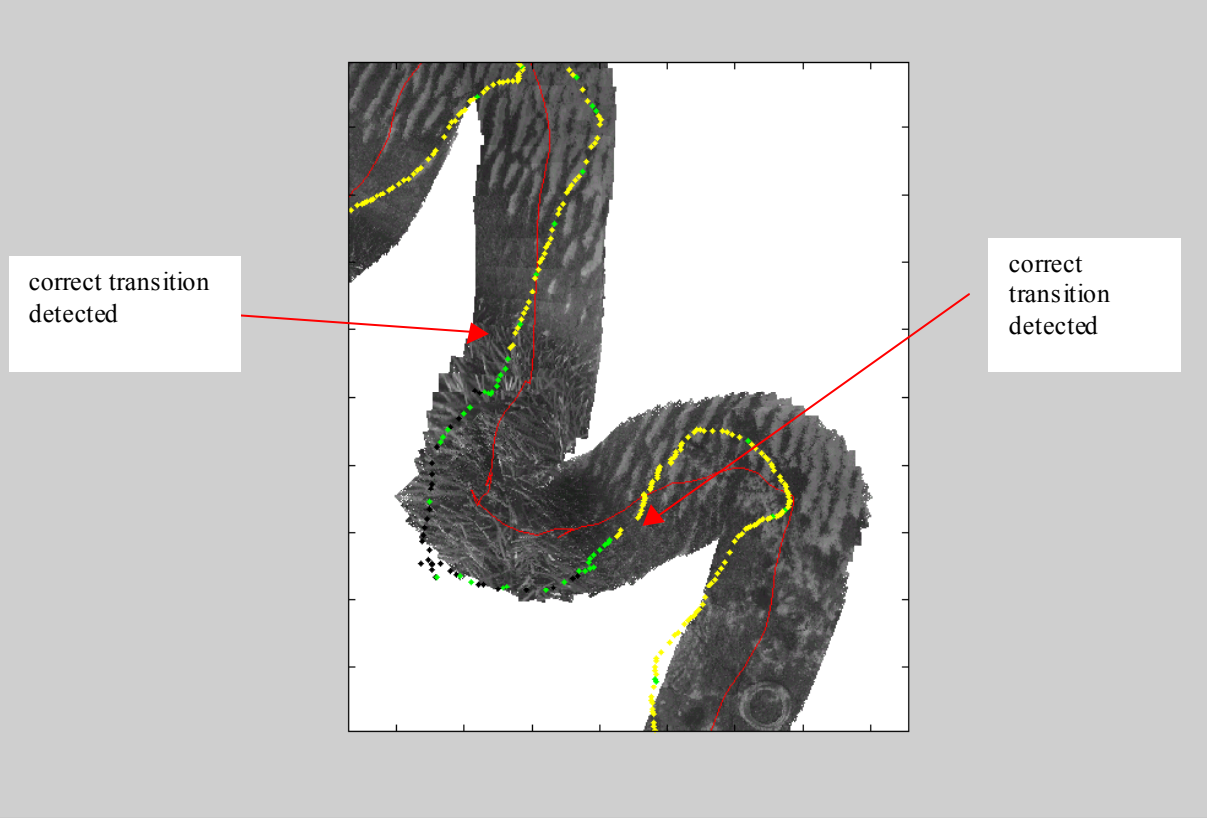

Figure 12: two transitions correctly detected.