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Counting of satellites with direct GNSS signals using Fisheye camera : A comparison of clustering algorithms

D. Attia and C. Meurie and Y. Ruichek and J. Marais

Abstract—This paper investigates the problem of accuracy of localization with GNSS in constraint environments. The ultimate goal is to provide a first confidence index on the accuracy of the position given by the GNSS. In this paper, we propose to use the complementarity between the GNSS signals and the development in image processing to count satellites with direct reception state. It consists to use a vehicle equipped with a GPS-RTK and a camera oriented upwards to capture images and count after repositioning, the satellites with direct signals (resp. with blocked/reflected signals) i.e. located in the sky region of the image (resp. located in the not-sky region). The proposed approach is based on an optimal clustering applied on simplified images. More preciously, the acquired image is simplified using a geodesic reconstruction with an optimal contrast parameter. Then, a clustering step is made in order to classify the regions into two classes (sky and not-sky). For that, a set of unsupervised (KMlocal, Fuzzy C-means, Fisher and Statistical region Merging) and supervised (Bayes, K-Nearest Neighbor and Support Vector Machine) clustering algorithms are compared in order to define the best classifier in terms of good classification rate and processing time. Experimental results are shown for hundred images taken in different conditions of acquisition (illumination changes, clouds, sun, tunnels, etc).

I. INTRODUCTION

Global Navigation Satellites Systems (GNSS), such as GPS, GLONASS, COMPASS and the new European GALILEO contribute widely to the localization and navigation systems in Intelligent Transport Systems (ITS) framework. Even if most of them give satisfying accuracy in terms of position of localization, they cannot avoid propagation problems, precisely in terms of multi-path phenomena of GNSS signals (mainly in constraint environments such as urban zones). Indeed, in dense environments, signals can be blocked (no signal received), shadowed (signal received after reflections without any direct ray) and direct. These constraints make tough the evaluation of received position reliability. The proposed approach in this paper sights on real time applications, notably ITS applications. For these reasons, our challenge consists of computing, in real time, a first confidence coefficient to each computed position, considering the complementarity that exists between computer vision and localization systems. For instance, we can notice that a computed position is reliable if we receive, at least, four direct signals. In the proposed approach, we investigate

the computed position inaccuracy by computing the number of satellites with signals having direct path using computer vision. In the framework of these works, a sequence of real images are acquired on mobility. Thus, a vehicle is equipped with a GPS and a Fisheye camera (characterized by a large field of view (180°) that can offer the possibility to have the majority of environment components), located on the roof and oriented upwards to capture images of the sky. Image processing consists of sky region detection. Then, the first step concerns image classification in two classes "sky" and "not sky" using supervised and unsupervised classification algorithms. Next step consists of repositioning satellites in classified images to compute signals having direct path. Experimental clustering and repositioning results using real data and an evaluation methodology are realized to prove the effectiveness and reliability of the proposed approach. The contribution of present works, with respect previous ones in [1], consists of testing of other sophisticating classification algorithms that can improve the results.

The paper is organized as follows: Section II presents the image processing step. Firstly, a description of the proposed method to simplify image is given. Secondly a description of used clustering algorithms (supervised and unsupervised) is then presented. A comparison between the obtained clustering results and the choice of the best classifier in terms of good classification rate and processing time are given in section III. Based on the satellites repositioning in the processed image, an evaluation of the satellites reception state is finally presented. Section IV concludes the paper and presents future works.

II. FISHEYE IMAGE PROCESSING

In this section, we present a strategy of image processing to detect the sky and other objects present in the image. If we refer to the literature, many color texture segmentation methods exist which aim to distinguish different objects in the image [2], [3], [4], [5]. However, few of them guarantee real time constraint. The proposed strategy is then based on two steps. The first one concerns a real time method using mathematical morphology and more precisely a geodesic reconstruction by dilatation (GRD) with an optimum parameter of contrast. This method allows us to simplify the input image before the second step which is clustering made in two clusters (sky and not sky).

A. FISHEYE IMAGE SIMPLIFICATION STEP

In previous works [3] and [2], a color and texture based segmentation technique which provides good results has been

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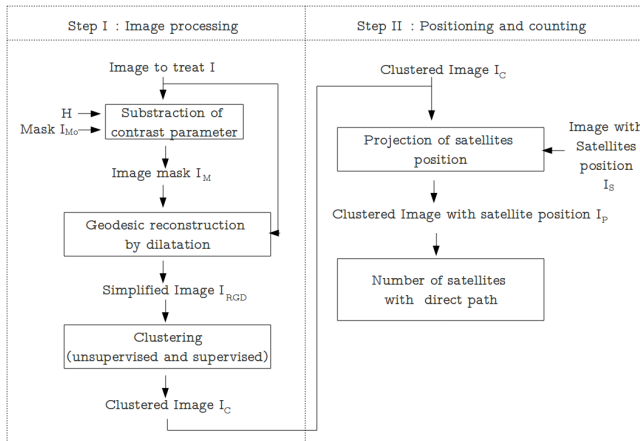


Fig. 1. Global synopsis of the proposed strategy.

proposed. However, its processing time is very high considering real time applications. In the context of our application, it is very important to diagnostic the satellite reception state in real time. For this reason, we propose in this paper a new strategy of image processing based on a geodesic reconstruction by dilatation with low processing time. Figure 1 shows the synopsis of the process. Let I be the color image to treat. Let H be the contrast parameter which indicates the level of peaks to be deleted. Let I_{M_o} be the mask of the used lens. Used in the geodesic reconstruction, the color image I_M is obtained by subtracting the parameter H at a color component of the initial image I (i.e. $I^{C_i} - H \times Id$ where I^{C_i} represents each color component, and Id is the identity matrix). The result of the geodesic reconstruction by dilatation is denoted I_{GRD} . Let I_p be the classified image with satellites positions. The choice of the geodesic operator is explained by his effect on the sky grayscale distribution. Indeed, as one can notice, image acquisition is done in different conditions (illumination variation, lack of stability of the camera due to the movement of the vehicle, etc). For this reason, it is interesting to homogenize the sky region by a geodesic reconstruction by dilatation. This smoothing operation is helpful for the clustering step since it deletes local bright peaks. The geodesic operator is expressed as follows:

$$\begin{aligned}
 (1) \quad I_{GRD} &= \bigvee_{(n \geq 1)} \delta_{I_M}^{(n)}(I) \\
 (2) \quad \delta_{I_M}^{(n)}(I) &= \delta_{I_M}^{(1)} \circ \delta_{I_M}^{(1)} \circ \dots \circ \delta_{I_M}^{(1)}(I) \\
 (3) \quad \delta_{I_M}^{(1)}(I) &= (I \oplus B) \wedge I_M
 \end{aligned}$$

where \oplus corresponds to the operation of morphological dilatation, B represents the structuring element and $\delta_{I_M}^{(1)}(I)$ is the result of the first rate geodesic dilatation [6]. $\delta_{I_M}^{(n)}(I)$ corresponds to the composition result (denoted by \circ) between first rate geodesic dilatations until idempotence (given by the n^{th} rate). \wedge corresponds to the intersection and \bigvee

indicates iterating successive first rate geodesic dilations [6].

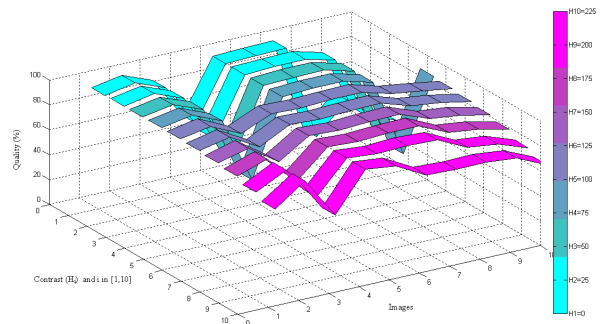


Fig. 2. Quality of the clustering with k-means algorithm according to the contrast parameter $H \in [0, 255]$.

In order to optimize the value of the contrast parameter H (that gives the best smoothing of sky region), we perform an exhaustive research on a dataset, which is composed by ten images acquired in different kinds of environment (urban and rural for example see images in figure 4). Figure 2 shows the results of the clustering rate according to the parameter H . In this figure, each band (colored differently) corresponds to a value of the contrast parameter H . One can notice, some drops at the first bands (i.e. of the first values of H) which can be explained by an insufficiency of H to homogenize the sky region for some images. If we consider all images, one can conclude that the best homogenization is obtained for this example with $H = 100$ (corresponding to H_5 illustrated in purple in Figure 2).

B. CLUSTERING STEP

In previous works [1], the k-means clustering algorithm has been tested on simplified image by GRD. Even if, one can notice that obtained results are satisfying, we have performed tests with other clustering algorithms existing in the literature. Indeed, we aim to check if there are other combinations of simplification and clustering which improve results. Four unsupervised (KMlocal, Fisher, Fuzzy C-means and Statistical Region Merging : SRM) and three supervised (Bayes, Support Vector Machine : SVM and K Nearest Neighbor : KNN) clustering algorithms are then tested. Before testing, a short theoretical introduction of each used clustering algorithm is presented in this section.

1) Unsupervised clustering:

- **KMlocal:** This algorithm contains four different versions of the k-means clustering. Three of these versions were developed to perform the known k-means algorithm which clusters a set of n data points (in our case image pixels) into k clusters (in our case two clusters sky and not sky) by minimizing the mean square distance between each data point to the nearest center. The first version is the classic Lloyd's algorithm (known also k-means algorithm which was used). Lloyd's algorithm starts from random sampled starting points

and repeats Lloyd's algorithm steps until a convergence condition. The second version of this algorithm is called Swap : this procedure makes a local search heuristic which speeds up the process of solution finding. This algorithm get stuck in locally minimal solutions that are far from the optimal. Third algorithm is called Hybrid due to the combination of the two previous versions Lloyd's and Swap. Hybrid version is more complex and makes a number of Swap steps followed by Lloyd's steps to perform Swap version. The last performing k-means algorithm is called EZ-Hybrid. The fourth version simplifies Hybrid algorithm by making one Swap iteration followed by some number of iterations of Lloyd's version. More details of KMlocal clustering algorithm can be found in [7] and [8]

- Fisher: This algorithm clusters data points into k clusters by dividing the grayscale histogram into k disjoint clusters which should have the minimum of variance sum (see [9] and [10] for more details).
- Fuzzy C-means: This algorithm clusters a set of data points in k clusters and it is a generalization of k-means algorithm. It is based on minimization of the mean square distance multiplied by a set of coefficients denoted u_{ij} in $[0, 1]$ called the degree of a membership x_i in the cluster j (cf. Equation 4). Fuzzy algorithm is also characterized by a fuzzy parameter m which fixes the degree of fuzzy of the algorithm. The fuzzy parameter is defined in the interval $[1, 2]$. When m tends to 1, one tends to k-means algorithm (see [11], [12], [9] and [10] for more details).

$$(4) \quad J_m = \sum_{i=1}^N \sum_{j=1}^C u_{ij}^m \|x_i - c_j\|^2$$

Where N is the number of data points and C is the number of clusters (c_j are centers of each cluster).

- SRM : Statistical region merging is a clustering approach based on a novel definition of image pixels disposition. The algorithm starts by defining adjacent pixels couples denoted (p, p') . The set of these couples is denoted S_I where I is the image to cluster. Then, this set of couples S_I will be sorted in increasing order of $f(p, p')$ which is a real-valued function. Then, this order will be traversed only once. For each current couple of pixels $(p, p') \in S_I$ which have not the same cluster label : $R(p) \neq R(p')$, the merging criteria denoted $P(R(p), R(p'))$ is checked. The merging is made if this criteria is true. This algorithm is performed by the best choice of the real-valued function $f(., .)$ which gives the best clustering results. This technique is more detailed in [13], [14], [15].

2) *Supervised clustering*: In this subsection, we are interested to supervised clustering algorithms which need a learning step before clustering. The learning step is generally made on a given data points that we know the cluster of each data point (in our case learning step is made from the reference clustering image). This step allows us to define a

learning database and a decision function thanks to them we can cluster our data points. The performance of clustering results changes according to the size of learning database. For each supervised clustering algorithm, we give short definition.

- Bayes : This clustering algorithm is based on stochastic statistics using the theory of Bayesian decision. The density function which describes the degree of belonging of a pixel x into a C_i cluster takes Gaussian form. Bayes algorithm aims to determine for each given pixel his cluster C_i which maximizes the density proportion to contain a pixel x (see [9] and [16] for more details).
- KNN : The K nearest neighbors clustering algorithm consists on computing of a density proportion to evaluate the belonging pixel x of the learning database to C_i cluster. The density function is given by equation (5) and takes in consideration the k nearest neighbors as the name indicates it.

$$(5) \quad r_i(x) = \frac{k_i(x)}{n_i \times V(x)}$$

Where $k_i(x)$ is the number of pixels belonging at the same time to the C_i cluster and to the k nearest neighbors of x . n_i is the number of pixels of C_i cluster and $V(x)$ is the sphere volume of the k nearest neighbor points. Thus, the cluster of the pixel x is the maximum of $r_i(x)$ (see [17],[18] and [9] for more details).

- SVM : This algorithm was developed basically to cluster data points into two clusters. Thus, the main SVM algorithm goal is to find the clustering function that not only separates data points but also maximizes the distance between these two clusters [19]. This algorithm makes the learning step considering that data points are linearly separable if they are projected on the adequate space. This projection is made thanks to a set of functions known as kernel functions. Gaussian function is the most known kernel function in the literature. The resolution of the SVM problem returns to search the best hyperplane which makes the best separation of data points. This hyperplane will be represented as a linear combination of a points set from the learning database. These points are known as support vectors. The most known algorithm to solve the SVM problem is Sequential Minimal Optimization. The decision function is defined as followed [9]:

$$(6) \quad \varphi(x) = \sum_i \alpha_i y_i k(x_i, x) + b$$

where $0 \leq \alpha_i \leq C$ and (x_i, y_i) are examples from learning database.

III. EXPERIMENTAL RESULTS

Before comparing the classification results, we explain the evaluation method providing the percentage of visible sky correctly classified. From the simplified image obtained previously, a clustering process is performed using a set of supervised and unsupervised clustering algorithms. The goal

is to classify the image after simplifying it by GRD into two classes, which correspond to the sky and the rest of the image labeled as not sky (vegetation, buildings, tunnel, etc) and to determine how many satellites have direct path. For the evaluation, a reference classification is performed for 100 images. Several types of images are used in order to show the influence of experimental conditions of detection results. For example, one can notice in figure 4 images with high illumination (a, e and f), with dark illumination (g and h) and with clouds (c and d). For each classification result, five measurements are computed: 1/ the percentage of pixels that actually make part of the sky region in the classified image and in the reference image; 2/ the percentage of pixels classified as sky but do not make part of the sky region in the reference image; 3/ the percentage of pixels classified as not-sky in both images; 4/ the percentage of pixels classified as not-sky but do not make part of the not-sky region in the reference image; 5/ the five measurement, corresponds to the sum of the first and third measurements, can be viewed as the percentage of pixels that are correctly classified.

A. Clustering evaluation

In this subsection, we compare using the evaluation technique previously introduced, the clustering results obtained with seven of supervised and unsupervised clustering algorithms. Our goal is to choose the clustering algorithm which performs the global proposed strategy. In Table I, we summarize the evaluation of all clustering results (unsupervised and supervised). We compare clustering algorithms according to several factors: average clustering rate, computational time, optimal contrast parameter of GRD and optimal parameter corresponding to each clustering algorithm. It was previously mentioned that some clustering algorithms performance depends on parameters. Thus, we show exhaustive tests (using 100 images) for some clustering algorithms according to several parameter to optimize them. For KMlocal algorithm, exhaustive tests were made using four versions of performing k-means clustering to choose the best version that allows to have best clustering rates. One can notice that the best results are obtained by Swap version. Fisher algorithm is applied on grayscale image, we evaluate then clustering rates for each color component of RGB color space and the blue component gives best results. Fuzzy c-means algorithm is evaluated for different values of fuzzy parameter $m \in [1, 2]$ and $m = 2$ is optimal value. The last unsupervised clustering algorithm tested is SRM which has no parameter to vary. For best visualization, we present only results with best parameters and we compare them in figure 3 (a). The best clustering algorithm is SRM (curve drawn by purple in figure 3 (a)). However, it requires a computational time of 15s. The second one is Fisher with a computational time of 1s. These results are illustrated in figure 3 (a) and Table I.

The learning step of supervised clustering is fundamental to build the decision function. We should keep in mind that we have to find a compromise between optimal size

TABLE I
PERFORMANCE OF UNSUPERVISED AND SUPERVISED CLUSTERING ALGORITHMS ACCORDING TO COMPUTATION TIME AND QUALITY OF CLUSTERING.

Algorithm	Time (s)	Quality (%)	H optimal	Best parameter
KMlocal	1.42	95.59	20	Swap
Fisher	1.03	96.09	20	Blue component
C-means	4.32	95.92	20	$m = 2$
SRM	14.92	96.40	20	-
KNN	39.03	95.59	30	Nb = 100
Bayes	1.73	96.61	130	Nb = 75
SVM	5.42	92.18	20	-

of learning database and the complexity of the decision function. For both Bayes and KNN clustering algorithms, we use a database having different sizes and made up of images set with their known clustering references (from 25 to 100 images) to compute the decision function. One can notice that for KNN algorithm, best clustering rates are obtained with size equal to 100 images (see Table I). For Bayes algorithm, one can notice that there is not great changes of clustering results between 75 and 100 images. Thus, it is more performing to choose the size equal to 75 images. For SVM, the learning step is made differently. We select directly in the image to be classified two blocks from each region of interest of the smoothed image (sky and not sky). From these two blocks we have a set of pixels that we know their cluster of belonging. The decision function will be then computed using radiometric informations of each pixel. As it was made for unsupervised clustering results, we summarize results of supervised clustering in figure 3 (b). One can conclude that Bayes algorithm gives best clustering rates (curve drawn by blue in figure 3 (b)) with in average clustering rate equal to 96.61% and computational time around 1.73 seconds. If we compare unsupervised and supervised clustering algorithms, one can notice that Fisher algorithm gives the lowest computation time equal to 1.03s. However, in average Bayes gives the best clustering quality which is equal to 96.61%.

B. Satellites repositioning and number of satellites with direct path

In this section, we present the methodology to replace satellites in the original (Fisheye) images and in the classified ones (see figure 4). After that, we can identify satellites that are situated in sky region and satellites elsewhere. This allows to distinguish signals having direct path from others ones (blocked, shadowed). The step of satellites repositioning consists of three subtasks: 1/ data acquisition; 2/ data calibration and formatting; 3/ STK software platform. More details of this repositioning step can be found in [1].

The projection of satellites position on the clustering results is presented in figure 4. The first row represents original images with satellites position (in red). Other rows represent the classified images with best clustering algorithms previ-

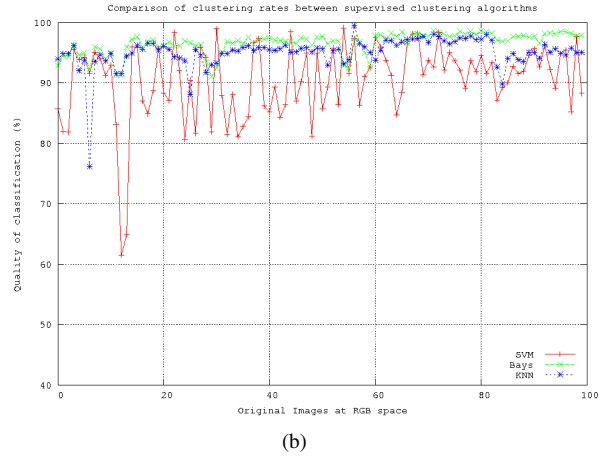
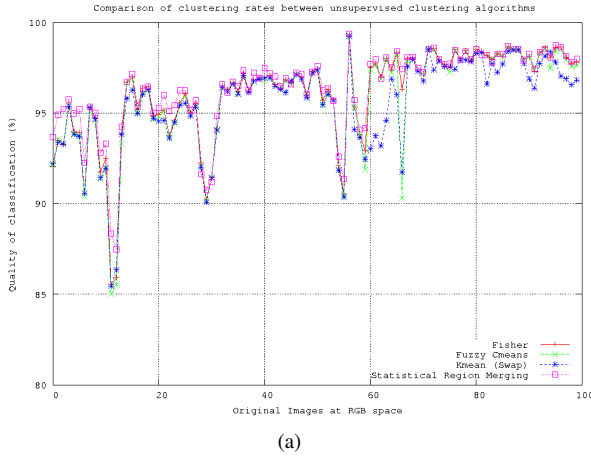


Fig. 3. Comparison between clustering algorithms : (a) evaluation of unsupervised clustering algorithms with best parameters, (b) evaluation of supervised clustering algorithms with best parameters.

ously selected (second row Fisher and third row Bayes). From the previous steps, we can determine the number of satellites with direct path. For this reason, the original and classified images with the satellites position are used to determine the satellites located in the sky region (GNSS signals with direct path) and the satellites placed elsewhere (GNSS signals blocked or shadowed). The evaluation process is performed using real dataset representing 100 images with different difficulties to demonstrate the effectiveness and the reliability of the proposed approach. Eight various examples of the dataset are presented in Figure 4. One can notice in original images (first row of figure 4) a rural environment ((a), (b) and (c)), an end of tunnel (d), an environment with buildings and vegetation ((e) and (f)) and finally a urban environment ((g) and (h)). In classified images, the sky region is represented in blue and the obstacles in brown, the reception state of each satellite (color is green if the path is direct vs red blocked or shadowed). According to the used clustering algorithm, table II summarizes the number of satellites with direct reception state in each image of figure 4. One can conclude that the reliability depends on the used clustering algorithm. For example, SVM algorithm gives false results for images (a) and (f). KMlocal algorithm gives false results for images (c) and (d). SRM provides good results for image (d). To conclude, if we consider three factors (real time application, quality of clustering and reliability), the best clustering algorithms to be selected are both Fisher (with computation time around 1.03 s, clustering rate 96.09% and reliability around 87.5%) and Bayes (with computation time around 1.73 s, clustering rate 96.61% and reliability around 87.5%). However, we favor Fisher algorithm which is faster. One can notice that processing time takes into account the evaluation step and depends strongly on image size.

IV. CONCLUSIONS AND FUTURE WORKS

This paper focuses on the problem of accuracy of localization with GNSS in constraint environments. In this paper, we have proposed to use the complementarity between the

TABLE II
OCCURRENCE SATELLITES WITH DIRECT RECEPTION STATE ACCORDING TO CLUSTERING ALGORITHM.

Algorithm	I_a	I_b	I_c	I_d	I_e	I_f	I_g	I_h	Reliability
KMlocal	4	4	3	0	4	3	4	3	75%
Fisher	4	4	4	0	5	3	4	3	87.5%
C-means	4	4	3	0	5	3	4	3	75%
SRM	4	4	3	0	6	3	4	3	87.5%
Bayes	4	4	4	0	4	3	4	3	87.5%
KNN	4	3	3	0	4	3	4	2	50%
SVM	2	4	4	0	4	2	4	3	62.5%
Reference	4	4	4	0	6	3	4	3	100%

GNSS systems and the development in image processing to count satellites with direct reception state. The proposed method is based on geodesic reconstruction by dilatation (with an optimal contrast parameter) coupled with adapted clustering algorithm. In this paper, a comparison between several unsupervised (KMlocal, Fisher, fuzzy C-means and SRM) and supervised (Bayes, KNN and SVM) classifiers has been developed in order to define the best one in terms of classification rate and computational time. One can conclude that the proposed approach (GRD coupled to Fisher clustering algorithm) offers a clustering rate of 96.09% VS 93.1% with Loyd's algorithm [1] and VS 89.6% with an approach combining color and texture informations [3]. Furthermore, this method respects real time constraint with a computational time of around 1 second per image. Future works concern the estimation of the confidence of positioning computation according to the number of satellites with direct and shadowed signals.

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REFERENCES

- [1] D. Attia, C. Meurie, Y. Ruichek, J. Marais, and A. Flancquart, "Image analysis based real time detection of satellites reception state," *IEEE*

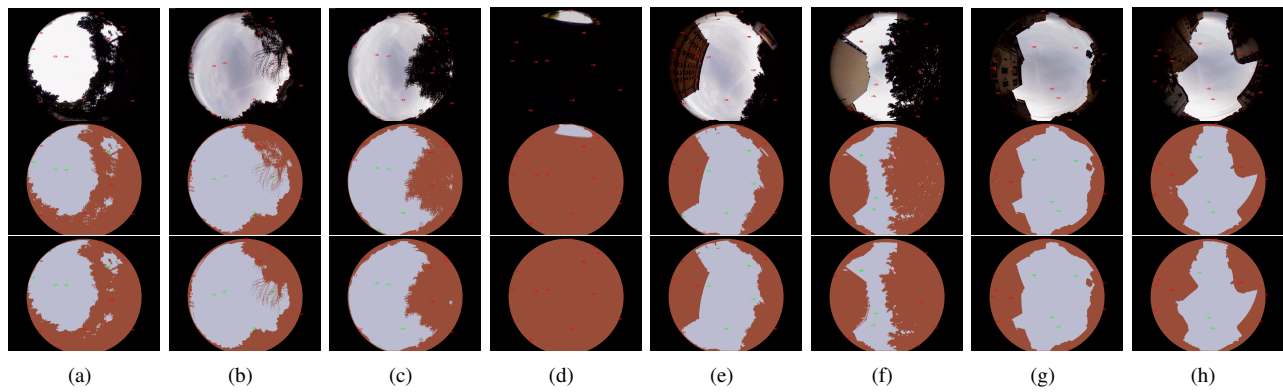


Fig. 4. Clustering results of the best unsupervised clustering algorithm and the best supervised clustering algorithm (first row: original images with satellites position, second row: Fisher clustering results and third row Bayes clustering results).

- International Conference on Intelligent Transportation Systems (ITSC) Island, Portugal*, pp. 1651–1656, 2010.
- [2] A. Cohen, C. Meurie, Y. Ruichek, J. Marais, and A. Flancquart, “Quantification of gnss signals accuracy: an image segmentation method for estimating the percentage of sky,” *IEEE International Conference on Vehicular Electronics and Safety (ICVES), India*, pp. 40–45, November 2009.
- [3] A. Cohen, C. Meurie, Y. Ruichek, and J. Marais, “Characterization of the reception environment of gnss signals using a texture and color based adaptive segmentation technique,” *IEEE Intelligent Vehicles Symposium (IV), San Diego, California*, pp. 275–280, June 2010.
- [4] K. Y. Song, M. Petrou, and J. Kittler, “Defect detection in random color textures,” *Image Vis. Comput.*, vol. 14, p. 667683, 1996.
- [5] L. Shafarenko, M. Petrou, and J. Kittler, “Automatic watershed segmentation of randomly textured color images,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 6, no. 11, p. 15301544, November 1997.
- [6] L. Vincent, “Morphological gray scale reconstruction in image analysis: Applications and efficient algorithms,” *IEEE Transactions on image processing*, vol. 2, pp. 176–201, 1993.
- [7] T. Kanungo, D. M. Mount, N. Netanyahu, C. Piatko, R. Silverman, and A. Y. Wu, “An efficient k-means clustering algorithm: Analysis and implementation,” *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol. 24, pp. 881–892, 2002.
- [8] —, “A local search approximation algorithm for k-means clustering,” *Computational Geometry: Theory and Applications*, vol. 28, pp. 89–112, 2004.
- [9] C. Meurie, “Segmentation d’images couleur par classification pixelaire et hirarchie de partitions,” Ph.D. dissertation, Universit de Caen, 2005.
- [10] C. Meurie, O. Lezoray, H. Cardot, and A. Elmoataz, “Comparaison de classifieur non-superviss pour la segmentation d’images couleur : application en imagerie biomdicale,” in *In International Conference on Image and Signal Processing*, 2003.
- [11] J. C. Dunn, “A fuzzy relative of the isodata process and its use in detecting compact well-separated clusters,” *Journal of Cybernetics*, vol. 3, pp. 32–52, 1973.
- [12] J. C. Bezdek, “Pattern recognition with fuzzy objective function algorithms,” *Plenum Press, New York*, 1981.
- [13] R. Nock and F. Nielsen, “Statistical region merging,” *IEEE transaction on pattern analysis and machine intelligence*, vol. 26, no. 11, p. 1452, November 2004.
- [14] —, “On region merging: the statistical soundness of fast sorting, with applications,” *IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, vol. 2, pp. 19–26, 2003.
- [15] R.Nock and F. Nielsen, “Grouping with bias revisited,” *Computer Vision and Pattern Recognition, 2004. CVPR 2004. Proceedings of the 2004 IEEE Computer Society Conference on*, vol. 2, pp. 460 – 465, 2004.
- [16] C. Meurie, G. Lebrun, O. Lezoray, H. Cardot, and A. Elmoataz, “A comparison of supervised pixel-based color image segmentation methods,” in *In International Conference on Signal, Speech and Image Processing*, Octobre 2003.
- [17] R.DUDA, P.Hart, and D. Stork, “Pattern classification,” in *Xiley Inter-science 2eme dition*, 2001.
- [18] D. Michie, D. Spiegelhalter, and C. Taylor, “Machine learning,” *neural and statistical classification*, vol. 6, pp. 84–106, 1994.
- [19] M. Hasan and F. Boris, “Svm : Machines vecteurs de support ou sparateurs vastes marges,” Versailles St Quentin, France, Tech. Rep., 16 janvier 2006.