



**HAL**  
open science

# Synthetic Aperture and 3D Imaging for Mine Hunting Sonar

Franck Florin, Franck Fohanno, Isabelle Quidu, Jean-Philippe Malkasse

► **To cite this version:**

Franck Florin, Franck Fohanno, Isabelle Quidu, Jean-Philippe Malkasse. Synthetic Aperture and 3D Imaging for Mine Hunting Sonar. Undersea Defence Technology (UDT) Europe 2004, Jun 2004, Nice, France. hal-00504862

**HAL Id: hal-00504862**

**<https://hal.science/hal-00504862>**

Submitted on 21 Jul 2010

**HAL** is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

# Synthetic Aperture and 3D Imaging for Mine Hunting Sonar

F. Florin F. Fohanno I. Quidu J.-P. Malkasse

Thales Underwater Systems

Route de sainte Anne du Portzic, CS 43814, 29238 Brest cedex 3, France

Tel: (33) 2 98 31 37 00

E\_mail: Franck.Florin@fr.thalesgroup.com

## Abstract

Modern mines have become very stealthy. Sonar designed to face this threat must use enhanced classification process. The classification decision process corresponds to the discrimination between Mines and Non Mine Bottom Objects (NOMBO). The need for enhanced classification is due to the increasing number of non-mine objects detected at the first step of the mine hunting operation. The classification must have a reduced ambiguity factor if a good performance is expected. The best way to overcome this difficult classification challenge in common operation conditions is to obtain high resolution and multiple aspects views of the object to be classified. These performance can be obtained by the use of new techniques now available for various existing systems as hull mounted sonar and unmanned underwater vehicles : synthetic aperture imaging and 3D object reconstruction. Some results obtained at sea are shown.

## 1 Operational evaluation of mine counter measure sonar

### 1.1 MINE COUNTER MEASURE OPERATIONS

Mine Counter Measure (MCM) is a general capability that can include several types of missions required to complete a specific operational intent [4] :

- General or detailed survey to prepare Mine Warfare (MW) operations,
- Surveillance or exploration to assess Mine Warfare risk,
- Reconnaissance and Mine avoidance to avoid mine threat,
- Clearance to sanitize,
- Masking and jamming to prevent mine action,
- Provocation and discredit to deceive mine logic.

The MCM efficiency can be measured by its rate of delivery for a given quality level. For instance, the time needed to solve one of the above MW problem, with a given confidence that risk is brought down to an acceptable level.

These MCM operations require resources (sonar, sweep, vehicle,...) that are necessary to fulfil the mission. These resources can execute some specific functions depending on what they are designed for. The functions can be considered of two kinds : invasive functions are devoted to obtain a specific effect on the mine or its logic, whereas non-invasive functions do not have any influence on the mine itself. For instance, neutralisation, destruction, mechanical sweeping, influence sweeping, acoustic silencing, degaussing are invasive, while bottom mapping, detection, localisation, classification and identification are non-invasive.

The definitions and separation of the elementary functions as detection, classification, etc. depend in fact on the resources that are considered. For instance, on a side-scan sonar it is commonly considered that detection and classification are proceeded together at the same time, while in Mine hunting sonar frontal mode, detection and classification are processed by separated operators.

## **1.2 SEARCH PHASE OF MCM OPERATION**

Considered as MCM resources, search systems aim at finding mines within a given operation time in a predefined zone. This search phase is in fact a general preoccupation in military operations that applies not only in Mine Warfare domain but also in many fields of application of the art of war [1].

On a predefined operation theatre, operational performances of the MCM search system depend on two points: the probability to find the mines and the time required to cover the zone. Normally, those two criteria are concurrent, that is, increasing the probability to find the mine leads to increasing also the mission time.

The general theory of search has defined the elementary steps of the search operation: target detection, target recognition, target localisation [1].

Similarly, mine hunting is classically considered as a three steps process: (1) detection, (2) classification and (3) identification (possibly followed by mine disposal).

This way of dividing the operation process in three steps could appear somehow arbitrary. However the various degrees of the decision process are associated to different levels of precision concerning the target knowledge [4]. Detection aims to find objects in the water column or on the sea floor which feature a high acoustic return i.e. mine like echoes (MILEC), and aims to eliminate most of non-mine returns, i.e. false alarm reduction. Classification uses the measured acoustical characteristics of the echoes (echoes strength and signature, dimensions, shadows) to eliminate most of remaining false alarms and keep mine like contacts (MILCO). The final stage, identification, confirms classification by a formal recognition of the MILCO as a mine, and collects a maximum of information on the mine (type of mine, country of origin, settings, etc.).

In fact each stage of the decision process in the search operation consists in deciding for each measurement sample (or set of measurement samples) to which hypothesis this sample is associated. Detection deals with simple echoes, classification with detailed a-scan or sonar images, identification with video camera or acoustic camera images. Due to the different natures of the considered measurements, the different levels of decision (detection, classification, identification) have different levels of performance concerning their capability to recognise mines.

For instance, the detection level may distinguish about 20 MILEC on a detection glimpse composed of more than 1000 000 independent cells. The classification process filters 3 possible MILCO among the 20 MILEC by using the 20 associated images composed of more than 2000 independent pixels each. The video identification finally finds the manta mine among the 3 MILCO.

## **1.3 PERFORMANCE OF THE SONAR SYSTEM: RISK, CLEARING PERCENTAGE AND INEFFICIENCY**

The sonar system performance at the output of the classification step can be evaluated by the residual risk (which is the probability that a mine within the field of operation has not been

classified as MILCO, compared to an initial risk of mine presence) within a given operation time on a predefined operation theatre. The performance can be evaluated, dually, by the level of risk within an operation time, or by the operation time required to obtain a given risk R. The quantity R represents the proportion of mines which are not going to be classified as such and which therefore, at the conclusion of the operation, are going to represent a risk for navigation.

But risk and classification operation time are insufficient to describe the performance of the search system. In fact, search is a component in a larger military operation. Detecting and classifying the mines as such are not the only purpose of the MCM operation. These steps are always followed by other operation phases. In a clearance perspective, they are followed by identification and mine disposal. In some other situations, as when using an autonomous underwater vehicle (AUV) for reconnaissance or exploration, the sonar detection and classification steps could be followed by a wide avoidance manoeuvre for the whole following fleet, in order to keep it away from the detected/classified mine field.

In this global perspective, considering the risk and the sonar operation time as the only criteria of sonar performance evaluation could lead in fact to very optimistic and false conclusions.

As new available sonar systems are now able to detect very stealthy mines, they also detect more and more small objects that can be assumed, in a first time, as being mines. A sonar system that rapidly detects and classifies any encountered object as a mine, would be given a very good performance evaluation when considering only risk and time of operation: in fact it is true that such a system detects and classifies any encountered mine with high probability. The only problem, which is in fact a huge limitation, is that, it will also declare as "mine" a large number of NOMBO (Non Mine Bottom Objects as rocks, empty bottles, washing machines or soda cans). The high false classification rate will not penalise the sonar operation but will induce failure and defeat of following operation phases: the identification phase or the manoeuvre of the fleet. The ROV used for identification will have too many objects to identify that will slow down its operation. The mine field estimated dimensions will be too high and that will induce a pointless and unnecessary avoidance manoeuvre for the fleet, or even worse, that could abort a force projection operation. So, the aim of the classification step shall be not only to classify mines as such, but also to reduce the number of pointless false detection alarms, in classifying NOMBO as NON MILCO objects.

In fact, considering the global operation of the marine forces leads to the introduction of an additional criterion for the sonar evaluation: the probability for a NOMBO to be detected and classified as a MILCO. This quantity represents the operational inefficiency, that is the proportion of NOMBO which are going to be declared pointlessly "MINE" and therefore will slow down the operation.

## **2 Performance of the classification function**

### **2.1 OPERATIONAL AND PRACTICAL CONTEXT OF CLASSIFICATION PERFORMANCE EVALUATION**

The detection is based on the simple echo level compared to the background noise (Detection Threshold), and the discrimination between MILEC and NON-MILEC is issued on the target

strength of the object. At the detection stage, any object having a target strength similar to those of the mines can be considered as a mine and is most often pointed out as MILEC.

When mines still used to be high target strength objects, the number of non-mine objects passed on to the classification step was relatively small and, as a result, the overall mine hunting effort was mostly dimensioned by the detection process. This has rather drastically changed now that modern mines have become very stealthy ; The ambiguity factor (see below) of the detection measure is high, and sonar systems, designed to detect stealthy mines, will now also hand over to the classification process many more small non-mine bottom objects, with mine-like target strength.

It is now commonly noticed that sonar able to detect let say  $-30$  dB index mines detect also a large amount of small objects with similar target strength. In that case the classification process has to face a large amount of MILEC that can be up to 5 object per  $100 \text{ m}^2$ . In these conditions the classical detection process is inefficient and the global search effort is transferred to the classification function.

Hence, the classification process is now called upon much more often than it was in the past, hereby increasing its share in the overall mine hunting effort. Considering a number of several hundreds detected objects per square nautical mile it becomes necessary to classify the objects as rapidly and as securely as possible in order to limit the global time to fulfil the MCM mission.

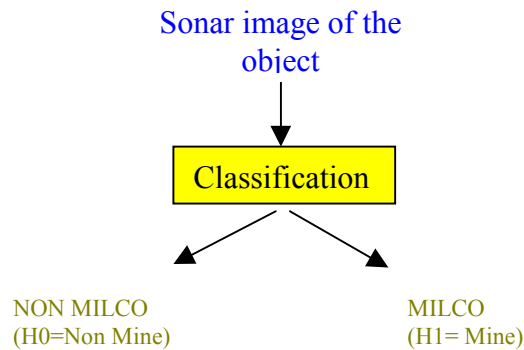
To realise the classification step two solutions can be used. The first method is long range echo classification, which can be performed with a long range detection sonar by analysing the echo signal structure (A-scan analysis). The second method is image based classification, which uses a more detailed acoustic image of the object, including both echo structure and shadow shape, given by a classification sonar that has a better resolution. This second method is in fact less ambiguous than the pure A-scan analysis and leads so to better performances.

The classification process is based on a sonar image analysis that includes both echo and shadow contributions of the object. The classification operation is described in figure 1 as a two hypothesis decision process. Considering this approach, the classification theory can be derived by today classical statistical mathematics for hypotheses testing (see Van Trees [5] for instance). This is very similar to the two hypothesis decision process of the detection theory. The difference with the detection stage lies in the input, which is now a sonar image of the object, and the two decisions, which are MILCO ( $H_1$ = Mine) or NON MILCO ( $H_0$ =Non Mine).

Formerly, as classification was a rather episodic process, it was not necessary to compute the efficiency of this step to determine the global performance of the mine search phase operation.

However, as the classification process has become a more time consuming exercise and is today the most critical step of both detection and classification, the precise evaluation of its performance becomes mandatory.

In previous papers [2], [3], a method was proposed, to evaluate the performance of the image based classification step. The method has been described through its theoretical and practical aspects. The main elements of this theory are recalled hereafter.



**Figure 1 - Classification decision process**

## 2.2 DEFINITION OF THE COC CURVES

Assuming that parametric statistical models are defined to describe the measured image under the respective hypotheses  $H_0$  and  $H_1$ , the performance of the classification can be described by the COC curves (Classification Operational Characteristic curves) of the sonar. These curves draw the dependence between probability of classification ( $P_c$  is the probability to decide that the image corresponds to MILCO knowing that the object is a mine) and probability of false classification ( $P_{fc}$  is the probability to decide that the image corresponds to MILCO knowing that the detected object is not a mine). COC curves are  $P_{fc}$ - $P_c$  graphs and are defined for a given sonar in well defined environmental conditions (grazing angle, range, reverberation level, shadowing, characteristics of NOMBO) and for a specific mine. In fact, it is obvious that the probability of classification depends on the mine type as the probability of detection does too.

These COC curves can be interpreted in an operational way.

$P_{fc}$  represents the proportion of NOMBO objects that will be classified as MINE and is a direct evaluation of the operational inefficiency of the classification (we could say as well that  $1-P_{fc}$  represents the operational efficiency). In practice  $P_{fc}$  has to be chosen in relation with the MILEC density (i.e. number of detected NOMBO per square mile) and with the global time period allocated to the MCM operation, as each false classification will bring about an ineffective identification and this identification will slow down the global MCM operation.

$1-P_c$  represents the proportion of MINES that will be classified as NOMBO and is a direct evaluation of the operational risk of the classification. This risk is of course critical as it represents the proportion of missed mines.

## 2.3 NOTION OF AMBIGUITY FACTOR

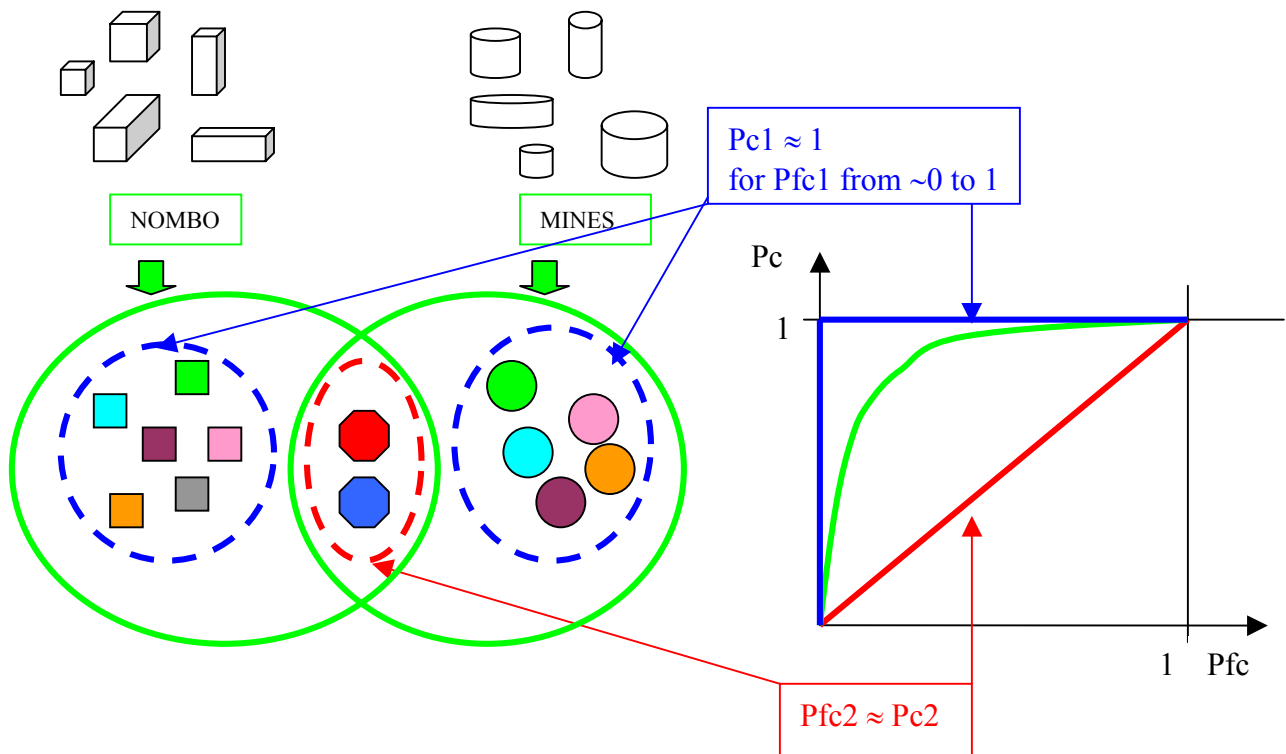
The different performance levels of detection, classification and identification are related to the different ambiguity factors of the corresponding decision problems. The ambiguity factor of the decision problem is the proportion of measurements corresponding to a possible Non Mine Bottom Objects (NOMBO) which have the same statistical characteristics than those of the searched Mines. For these ambiguous measurements, it is impossible to decide whether the object is a MINE or a NOMBO with a better decision process than the “monkey” one (the “monkey” decision process is the decision test that corresponds to the diagonal in the  $P_{fa}$ - $P_d$  or

Pfc-Pc graph, that is the test that has a false alarm rate equal to the probability of detection/classification).

Figure 1 shows the principle of the ambiguity factor for the classification process. On the figure, we see two groups of objects, MINES and NOMBO. The goal of the decision process is to determine if the measures correspond to a MINE or a NOMBO.

The different objects generate multiple statistical laws for the measurements. Each law is figured by a coloured form. The rounds correspond to the laws that represent measures issued from the mines only. The squares represent the laws of the NOMBO only. The octagons are the laws that describe indifferently a MINE or a NOMBO.

For the law within the red set (the octagons), it is mathematically impossible to distinguish with a good performance between the NOMBO and the MINE. The corresponding Pfc-Pc COC curve is drawn in red on the diagram (diagonal line, “monkey” decision process). For the measurement in the blue sets (rounds and squares) the performance can be better, assuming that the right decision test is designed. In this case the performance could tend to the ultimate performance represented by the blue curve on the diagram. The mean performance for the discrimination problem between MINES and NOMBO is represented by the green curve on the diagram. This curve is necessarily somewhere between the red and the blue curves.



**Figure 2: Principle of the ambiguity factor**

The mean performance ( $P_{fc}$ ,  $P_c$ ) for the global decision problem can be approximated par the following equations where  $\alpha$  is the “ambiguity factor”.  $\alpha$  is comprised between 0 and 1, and represents the proportion of not discernable decision problems.

$$P_c = (1 - \alpha)P_{c1} + \alpha P_{fc2} \quad (1)$$

$$P_{fc} = (1 - \alpha)P_{fc1} + \alpha P_{fc2} \quad (2)$$

For instance, if the proportion of NOMBO that can be discriminated from the mine is 20%, two situations can be considered. First, if we want  $P_{fc}$  to be less than 1% (for instance), it becomes impossible to get a value of  $P_c$  greater than 81%. Second, if we want  $P_c$  to be higher than 95%,  $P_{fc}$  shall be higher than 15%.

## 2.4 SONAR IMAGE AND MASK MODEL

The evaluation of the classification process requires the possession of a model and a database of measurements from mine and non mine objects. A model and an associated technique for classification performance evaluation called DMC (Delta-Mask Classification) have been introduced in previous papers (see Florin and al. [2], [3]).

A sonar image contains namely three kinds of pixels: reverberation, echoes, and shadow. Each pixel category can be given a statistical distribution function or equivalently a probability density function. This function describes the statistical behaviour of the pixel, that is, roughly, the probability that the pixel takes its numerical values within a given interval.

The statistical behaviour of an image can be represented with a 2D mask (or grid). Each square of the grid corresponds to a pixel of the image and includes the index number of the statistical law associated to this pixel (see Figure 3).

Using the theoretical mask of a known object in hypothesis  $H_1$  (if the object is the mine) or  $H_0$  (if it corresponds to a NOMBO) the Neyman-Pearson hypothesis test comes down and allows to compute the COC curves, using the concept of Delta-Mask. The Delta-Mask is simply the difference between the mask of the NOMBO and the mask of the MINE.

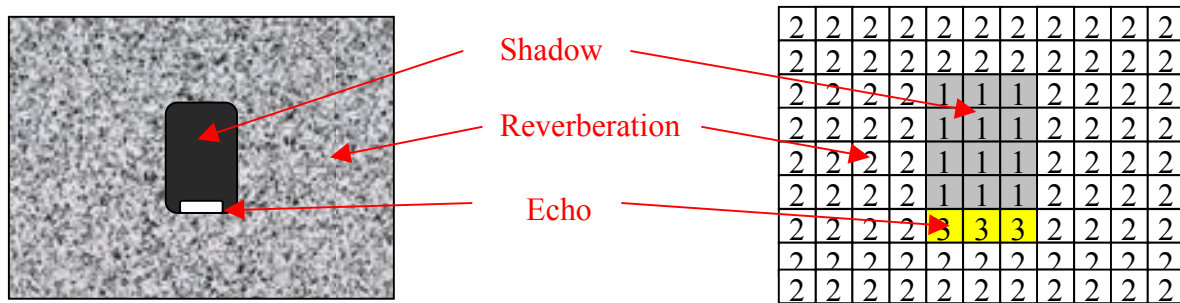


Figure 3 – Sonar image and the corresponding 2D mask

So, for given SONAR characteristics (range and beam resolutions, grazing angle, noise, reverberation, and echoes measured powers), a given MINE and a given NOMBO, the related COC curve can be computed, which gives the maximal performance of the classification capability of the sonar (see [2] or [3]).



### **3 How to increase classification performance**

#### **3.1 REDUCTION OF THE AMBIGUITY FACTOR OF THE CLASSIFICATION PROCESS**

The ambiguity factor of the image based classification process is determined by the proportion of Delta-mask that are empty. That is in fact the proportion of decision case where the mine and the NOMBO have identical masks (except the undetermined pixels).

This proportion is increased when the resolution of the sonar is low. In that case, any objects of the size of a few number of pixels are perceived in the same manner. In fact a first way to reduce the ambiguity factor is to increase resolution. Due to uncertainty in shapes and bottom profile, a resolution of about 5 cm could appear as a practical experienced value for good classification. This resolution can be achieved in the range dimension by increasing the bandwidth of the sonar. A 5 cm resolution in range requires a bandwidth of at least 15 kHz which is currently available on new MCM sonar. To get a 5 cm resolution in the beam-width dimension requires either to increase the frequency or the array length of the sonar, or to decrease the range. For instance, 5cm resolution corresponds for a range of 100m at about 500 kHz to an array length of more than 6 m.

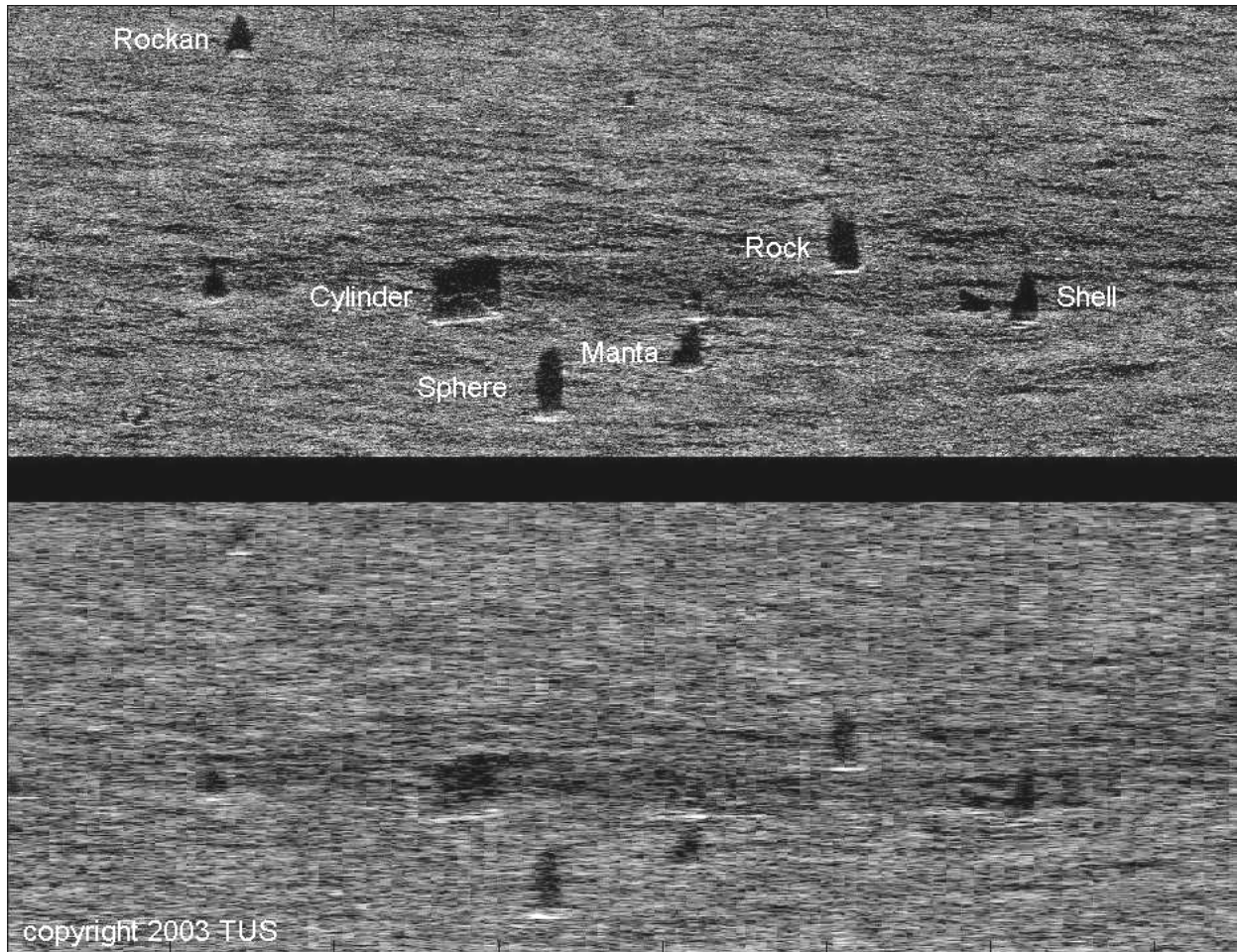
A second way to decrease the ambiguity factor is to increase the number of pixels describing the object by taking several views of the same object with different aspects. This is the multi-aspect capability. When comparing two objects, the different aspects of each object can be used simultaneously and so decrease the possible confusion. It could be sufficient in many case to limit the number of aspects to three views separated by intervals comprised between 30 and 45 degrees in azimuth. However it is also possible to use the whole 180° rotation information with a 3D reconstruction (see below). In that case the 3D reconstruction which uses all the available information can discriminate two objects that could have similar 2D sonar images in some conditions.

#### **3.2 SYNTHETIC APERTURE SONAR PROCESSING**

The Synthetic Aperture Sonar (SAS) processing can be used to increase the beam resolution of the sonar image, without increasing the length of the physical array. The technique requires the integration of several transmitted and received pulses, an improved beam-forming processing and a specific autofocus algorithm that compensates for the unwanted displacement of the array during its movement. More details can be found in [6] .

The technique is now available for operational sonar systems. Figure 4 shows the picture obtained with a TSM2022 MK3 hull mounted sonar. It has been used in a side scan mode to allow to perform synthetic aperture. The range span is comprised between 150m and 200m. The width of the image is here of about 40m.

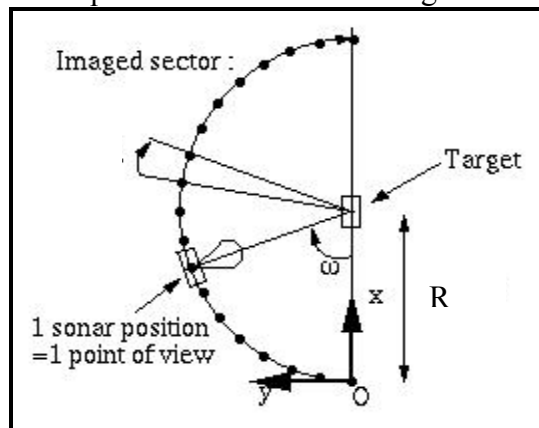
The classical image and the synthetic one are drawn on the same figure in order to allow comparison. The beam-width resolution of the synthetic aperture image is about 5 cm. The types of the various objects present on the image are indicated. It is obvious that the resolution improves the classification capability by giving more details on the object. For instance MANTA and ROCKAN mines can be distinguished by the structure of the echo on their body on the SAS picture, the Sphere and the Rock are also distinguishable by the two “horns” on the Rock shadow on the SAS picture, while the ambiguity is greater on the classical image.



**Figure 4: Synthetic and classical side scan apertures with a TSM2022 MkIII between 150m and 200m range**

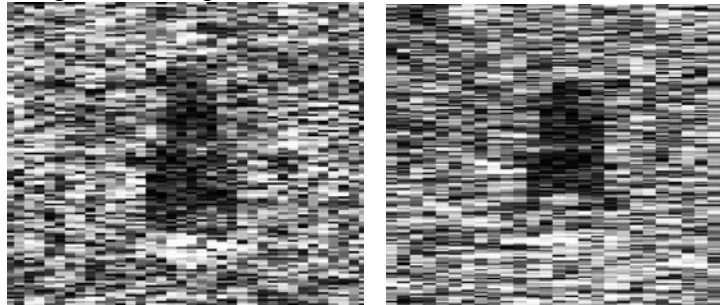
### 3.3 3D RECONSTRUCTION

The 3D reconstruction technique was described in a previous paper (see Malkasse [7]). The technique consists in getting several sonar pictures of the same object through a  $180^\circ$  pass around the object. The principle of the acquisition is described on figure 5.

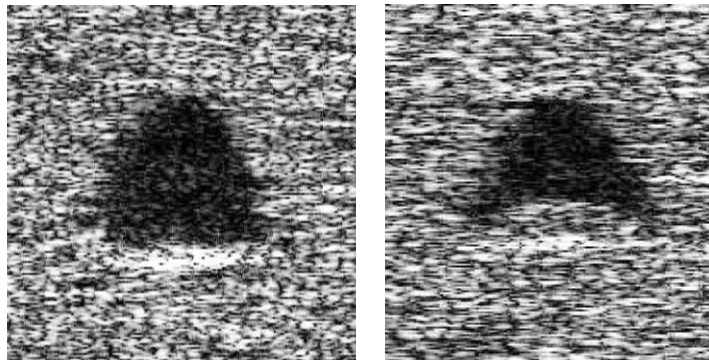


**Figure 5: Principle of 3D data acquisition**

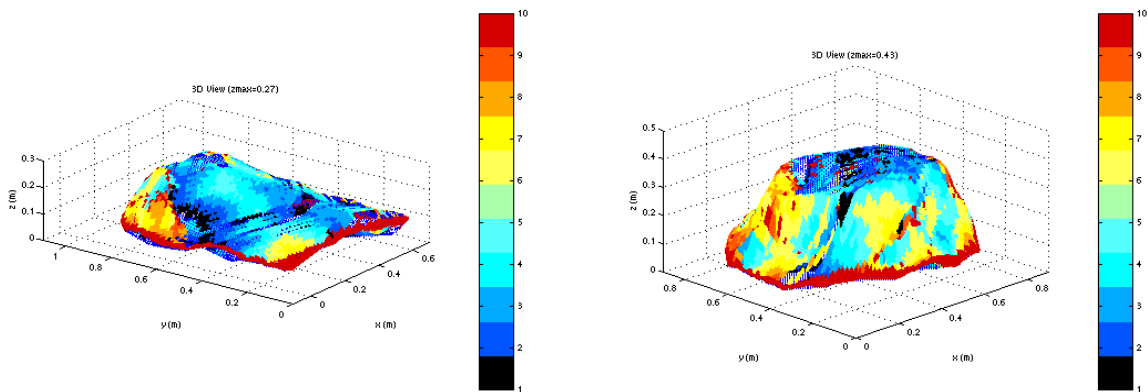
The reconstruction has been experimented at a range R of about 70 metres. Various objects have been acoustically reconstructed. Figure 6 shows two 2D raw images of a MANTA and a ROCKAN. It is difficult for a non-experienced operator to distinguish between the two mines. Figure 7 shows the same objects with SAS processing and Figure 8 shows 3D pictures of the mines after reconstruction. The colour code indicates the confidence level in the position of each point of the object due to the reconstruction process assuming the shadow estimation is perfect. It is easy even for a non experienced operator to define which is which.



**Figure 6: Raw images of MANTA & ROCKAN mines**



**Figure 7: SAS images of MANTA & ROCKAN mines**



**Figure 8: 3D reconstructions at 70 m of the MANTA & ROCKAN mines**

This experience proves that the multiple aspects data acquisition decreases the ambiguity of the classification process.

## 4 Conclusion

The success of the search phase in MCM operations is now conditioned by the performance of the classification. This performance is increased by high resolution and multiple aspects acquisition. Synthetic aperture processing is the only way to maintain the high resolution at long range. The technique is however available now and shall be mandatory for an increased number of MCM sonar systems.

## 5 Acknowledgement

The work presented here was realised under the French Government DGA (Délégation Générale pour l'Armement) A 99 77 120 contract number. The authors thanks very much French Navy (Marine Nationale), DGA/SPN (Service des Programmes Naval) and DGA/GESMA (Groupe d'Etudes Sous-Marines de l'Atlantique) for their support during the study.

## 6 References

- [1] B. O. Koopman, Search and screening, General principles with historical applications, Military Operations Research Society, Alexandria, Virginia, 1999.
- [2] F. Florin, F. Van Zeebroeck, I. Quidu and N. Le Bouffant, Classification performances of Mine Hunting Sonar: theory, practical results and operational applications, Proceedings UDT Europe 2003, Malmö, Sweden, 24-26 June 2003.
- [3] F. Florin, I. Quidu, N. Le Bouffant, Shadow classification performances evaluation of Mine Hunting Sonar, Proceedings UDT Asia 2003, Singapore, 9-11 Novembre 2003.
- [4] F. Duthoit, The future of Mine Counter Measure, Technical note, Thales Underwater Systems.
- [5] H. Van Trees, Detection, Estimation and Modulation Theory, Part 1, John Wiley & Sons, New York, 1968.
- [6] D. Billon, F. Fohanno, Theoretical performance and experimental results for synthetic aperture sonar self-calibration, Proc. OCEANS 2002, Biloxi, USA, October 2002.
- [7] J.P. Malkasse, Identification tool by sonar means with synthetic aperture sonar and 3D reconstruction, Proc. UDT Europe 2000, London, June 2000.