A new concept for mine-like object identification that is how to use imagery information

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***Abstract*—This paper presents a new concept for mine-like object identification. It is postulated that imagery information coming from the sources used for identification as the reference must undergo evaluation process. It has been simulated that, in extremely hostile conditions, even the most reliable source may supply the system in false information.**

Therefore it is suggested that information acquired from all sources (including the reference) should be subjected to the fusion process.

For the purpose of the presented considerations a new criterion of identification has been delivered.

I. Introduction

Nowadays systems of mine-like object (MLO) identification usually require a mine searching platform to perform at least two rounds for complete mine recognition [1], [2], [3]. During the first one processes of detection and classification are carried out, whereas the second one is intended for identification. The identification in most of the cases is done by a specifically trained frogman, who after taking observation makes the final decision whether or not the object of interest is the mine [4]. The efficiency of such ultimate settlement depends on many factors like observation conditions (including water transparency), human perception possibilities, and also experience in MLO recognition of the particular diver.

Experiments in application of new technologies in this area usually aim at replacing human being with remotely-operated platform [5], [6], equipped with video cameras, in order to reduce the risk of loss of the human life. Unfortunately, both of these techniques do not take into account the imperfectness of the reference (human or machine), which is presumed to be flawless. Reality shows that the human can be wrong, as well as the machine, no matter if it is human-operated or autonomous. Therefore an extra step: evaluation of the reference reliability [7], [8] is required in order to avoid the decision corruption.

Development of the AI causes that solutions based on autonomous platforms become more and more attractive [6], [9], since human perception constrains do not apply, while the expert MLO recognition knowledge can be algorithmized and implemented in the platform inference engine. Taking this into account the reason for splitting mine recognition process in two (or more) stages no longer exists, since information gathered from all sensors may be associated, evaluated, and combined by one fusion center. In such case the decision may be made immediately, just after the fusion is performed. Then, the following question may be raised: "How the reference information should be treated: as typical participant of fusion or any privileged one?". In the literature there exist solutions [10], known as *relative conditioning rules* for fusion of uncertain information with information of significantly higher degree of certainty (but still imperfect), which easily may be applied.

II. Mine-like object information model

Considering any MLO as an information object the following attribute table can be used in order to fully characterize that object [2], [3]. Table I encapsulates all the important knowledge about the MLO required for the tactical purposes. In the classical reconnaissance all these values are being fulfilled successively during detection, classification, and identification processes.

TABLE I
Concept lexicon used in MLO recognition system

Name	Value
ObjectType	{MILCO, MINE, OBSTRUCTOR, UNDEFINED}
GeneralPlacement	{UNKNOWN, ANCHOR, BOTTOM, DRIFTING, UNDEFINED}
SpecificPlacement	{UNKNOWN, SHALLOW, DEEP, UNDEFINED}
Mass	{UNKNOWN, $\leq$500kg, $>$500kg, UNDEFINED}
Activity	{INACTIVE, ACTIVE, UNDEFINED}
Purpose	{GENERAL, OPM, ZOP, HYDROACOUSTIC_REFLECTOR, UNDEFINED}
Sensitivity	{STANDARD, SENSITIVE, UNDEFINED}
GeneralContact	{NON-CONTACT, CONTACT, UNDEFINED}
SpecificContact	{UNKNOWN, ACOUSTIC, HYDROSTATIC, MAGNETIC, ANTENNA, UNDEFINED}
SpecificContactDetails	{UNKNOWN, AUDIO, LOW_FREQUENCY, HIGH_FREQUENCY, VERTICAL_COMPONENT, HORIZONTAL_COMPONENT, COMPLETE_MAGNETIC, UNDEFINED}
Sequence	{UNKNOWN, SEQUENCE, IMPULSE_SEQUENCE, COMBINED, TUPLE_NUMBER, DELAY, UNDEFINED}

Unfortunately, some of these attributes are not available for observation, and even a perfectly trained diver is incapable of defining them all. That means that in practice the complete identification (including such details as precise detonator specification) is never reached. Therefore it is suggested to concentrate on first four attributes, namely: *ObjectType*, *GeneralPlacement*, *SpecificPlacement*, and *Mass*, which can be assessed by visual sighting, and in the authors' opinion are the most important from the tactical point of view.

From the information point of view this kind of selection may be critical for any visual observation source, since much more information, however tactically irrelevant, may be retrieved through optical sensors. Therefore it is suggested to treat the reference visual information source as a regular participant of the fusion.

Since the identification, defined in terms of Table I, is unachievable, the authors have suggested a new concept of identification, which can be applied practically in decision making process. According to that concept, the identification is simply comprehended as a sort of "classification precise enough" for decision making, while the particular value of precision is calculated in the evaluation stage, mentioned in Introduction. If the calculated precision situates above the preset threshold value the object may be regarded as identified. Otherwise, it is considered an unidentified, and further operational investigation should be involved.

For the purpose of the considerations presented in this paper the following MLO information structure has been established.

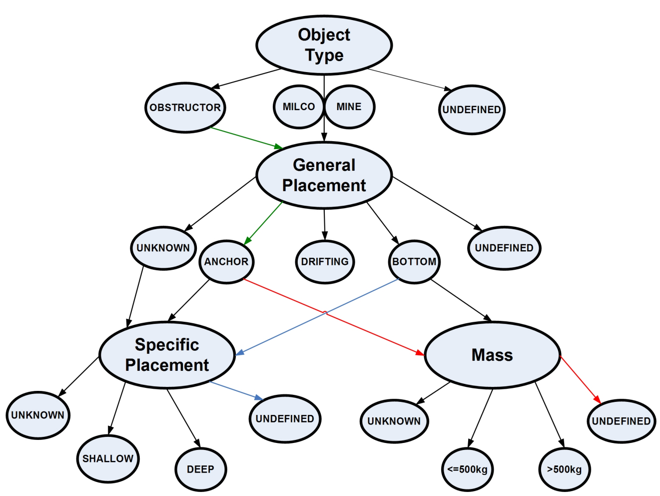

Figure 1. Hierarchical MLO information structure

Figure 1 shows the hierarchical relation tree, where the hierarchy results from the logical structure of the attributes. Namely, *ObjectType* is the most informative attribute, which defines the core of the representation of MLO, while the rest of the attributes is used to provide more details on it. Black arrows denote typical directions of inference, whereas red, blue, and green arrows define routes of inference referring to specific objects of attributes determined arbitrarily. For instance: for any anchor mine (red color) the value of the attribute *Mass* is predefined arbitrarily as UNDEFINED, since the *Mass* is only used to characterize bottom mines. Similarly: for any bottom mine (blue color) the value of the attribute *SpecificPlacement* is predefined arbitrarily as UNDEFINED, since that very attribute is used only to characterize anchor mines. In case of OBSTRUCTOR only one reasoning path has been defined, the same way as for the anchor mine, since the obstructor by definition is a minesweeper countermeasure object, acting as an anchor mine.

III. Simulation of the source information

Simulation of the source information is a very important issue, which should be considered during elaboration of the MLO recognition concept. Even though input information does not perform a direct part of the system, it does influence significantly on its architecture.

Considerations presented in this paper have been taken on the level of information (not data) processing, aiming at facilitation of creating the *Situation Awareness* [11], [12] in order to enable the operator decision making. Therefore the simulation should have also been performed on the information level. That means that no physical devices have been emulated, as well as no real input signals, with respect to any concrete transmission protocol, have been analyzed. Simulation was subject to information (comprehended by human), which could have originated from sensor subsystems (composed of detectors and classifiers).

Simulation has been taken in two stages:

– generation of mine-like objects;
– simulation of uncertain incomplete source information;

Generation of MLO has been based on initialization of its information representation of given characteristics with respect to MLO model in simulation space. These characteristics had been defined according to a finite set of values, determined by MLO ontology. For each of possible simulation scenarios declarations of responses of the particular sensor subsystems: sonar, gradiometer, and video camera have been predefined respectively.

Simulation of uncertain incomplete source information has been based on supplying the system with these predefined response declarations. The declaration in itself performed a probability distribution among possible classification hypotheses, provided by the particular source with respect to its ontological limitations.

IV. Mine-like object recognition model

Mine-like object recognition model defines processes required for creation of *Situation Awareness* for the purpose of decision making. It manages multiple subprocesses like: acquiring information from the sources, correlation of the acquired information with information already existing in the system, creation of MLO classification hypotheses, validation of the created hypotheses, evaluation, and calculating probabilities required for decision-making.

Certainly, some of the above mentioned perform complex separate problems, not entirely related to the fusion issues.

Therefore in the following subsections only the closely associated to fusion and identification problems, will be discussed.

A. *Information correlation*

Correlation of the acquired information with other information, already existing in the system, enables to decrease significantly redundancy in databases, and in the consequence to prevent from system overloading. It is worth of notice that for the purpose of this paper the term "correlation" is comprehended as an operation of finding linkage among datasets, not as a specific operation of data generalization, like in tactical links (e.g. Link-16) [13], [14], [15].

In the presented model the correlation takes place immediately after acquiring information from the sources and refers to:

– sources (*source correlation*), which leads to information update
– data/information (*data/information correlation*), which in turn leads to information fusion.

In case of the source correlation it is being verified if the source identifier of the currently processed MLO is identical with any of the source identifiers referring to the MLOs already existing in the system. If the verification is positive the processed MLO follows the position verification. If the positions are corresponding (with respect to the presumed tolerance) information update is proceeded, i.e. the previous source information (time stamp, exact position, etc.) is overwritten with the currently processed. If any verification fails a new MLO is initiated in the system and added to the MLO source list.

The information correlation follows directly when the source correlation is finalized. Unlike the source correlation information correlation operates on the fusion list, that is the list of MLO which have already been processed. In situation where at least two MLOs are of the same positions (with respect to the presumed tolerance), after the fusion is performed, they are treated as one and only one record is introduced to the fusion list. This record contains such information like time stamp, current position of the fused object, attribute values of the fused object, and the list of all fusion participants. "Individual" MLOs, that is MLOs which cannot be correlated with any other from the source list are rewritten directly to the fusion list. Thus the fusion list contains the complete set of the classified MLOs, and should be regarded as the main list the operator works on.

For simplicity, kinematic information fusion has been realized with usage of the rule of the representative, since the main effort of the research described in this paper is laid on the MLO identification, not the state estimation.

B. *Definition of classification hypotheses*

Information acquired from the sources are expressed with usage of the *concept lexicons* [12], [16], [17] used by classifiers corresponding to the particular sources. Thus, considering diverse types of sensors it is justified to assume they are ontologically different. Classes distinguished by the particular sources perform prior hypotheses, and they result directly from the characteristics of the utilized detectors and classifiers. Table II presents an example of such hypotheses, defined for the side sonar.

TABLE II
EXAMPLE PRIOR HYPOTHESES DEFINED FOR THE SIDE SONAR

Hypothesis	Code(*OT,GP,SP,M*)	Description
H_0	{1,1,10,10}	unknown MLO
H_1	{2,1,10,10}	unknown mine
H_2	{1,2,2,10}	shallow-water anchor MLO
H_3	{1,3,10,1}	bottom MLO
H_4	{3,1,10,10}	obstructor
...	...	...
H_n	{10,10,10,10}	undefined object

If observations are performed by multiple sources it is probable that they provide information referring to the same MLO. In such case, in order to unify the tactical view, a fusion mechanism is performed, which in turn results in creation of the secondary hypotheses, as a product of prior hypotheses, already existing in the system. Table III performs a hypothesis table for combination of information acquired from two sensors: S_1 and S_2.

TABLE III
HYPOTHESIS TABLE FOR TWO SENSORS: S_1 AND S_2

S_2 \ S_1	{1,1,10,10}	{1,2,2,10}	{1,3,10,1}	...	{3,1,10,10}
{1,1,10,10}	{1,1,10,10}	{1,2,2,10}	{1,3,10,1}	...	{3,1,10,10}
{1,2,2,10}	{1,2,2,10}	{1,2,2,10}	{1,X,2,1}	...	{3,2,2,10}
{1,3,10,1}	{1,3,10,1}	{1,X,2,1}	{1,3,10,1}	...	{3,3,10,1}
...	...	...	...	...	...
{3,1,10,10}	{3,1,10,10}	{3,2,2,10}	{3,3,10,1}	...	{3,1,10,10}

Blue color depicts an example secondary hypothesis, which as mentioned does not reside in the ontology of any of the sources. In this very case it denotes a shallow-water obstructor, that is the object of structure similar to an anchor mine, however unlike the mine it is not filled with explosives, and its purpose is minesweeper countermeasure. It is worth of notice that separately none of the sensors enables such precise MLO interpretation.

C. *Hypothesis validation*

The created secondary hypotheses should undergo verification, which is to define if they are possible in reality (i.e. attribute values are mutually consistent) or not. An example of logically inconsistent hypothesis has been presented in Table III assigned with a label {1,X,1,1}. Red color depicts abstract hypotheses of contradictory attribute values.

Except of the obvious unreal hypotheses also hypotheses specifically defined by the user may be erased, as required in this stage. As hypothesis validation is open for custom user modification, it gives an opportunity to utilize expert knowledge in such fields as: underwater weapon, acoustic detection, magnetic detection, and visual observation. By appropriate definition of acceptable secondary hypotheses possible information conflicts may be resolved instantly.

An example of user-defined inconsistent hypothesis has been presented in Table III assigned with a label {3,3,10,1}. At first glance, the statement seems to be correct as information that the MLO is OBSTRUCTOR may be easily associated with other information that the MLO is BOTTOM-placed. However, after realizing the definition of the obstructor and its similarity to an anchor object it becomes obvious that these two evidences do not fit to each other, and the hypothesis {3,3,10,1} should not be taken into account in further considerations.

D. Calculation of recognition probabilities

After reading sensor data declaration of probabilities referring to subsequent hypotheses are being made. As the hypotheses encompass multiple MLO features these probabilities should be calculated with respect to the values of MLO attributes.

In the proposed solution the above mentioned recognition probabilities have been calculated according to the following formula:

$$P(M_i|M_k) = P_{OT}(M_i|M_k) \cdot P_{GP}(M_i|M_k) \cdot \\ \cdot P_{SP}(M_i|M_k) \cdot P_M(M_i|M_k) \qquad (1)$$

where:

i denotes MLO index: $i = 1, 2, \ldots, N$;

N denotes number of detected mines;

k denotes simulated mine index (i.e. M_k denotes simulated mine);

OT, GP, SP and *M* denote: *ObjectType, GeneralPlacement, SpecificPlacement,* and *Mass*, respectively.

This denotes that for any MLO hypothesis the resulting probability performs a product of partial probabilities referring to that MLO hypothesis.

Even though the order of the attributes and their semantics indicate a sort of hierarchy, where *ObjectType* performs the most important attribute, the operator of multiplication in the formula (1) makes each of the attribute introduce potentially identical contribution to the resulting recognition probability. This operation is intentional and comes from the fact that the tactical meaning of the particular contributor does not have anything to do with conditioning of measurements. Thus, although *SpecificPlacement* may seem to be less important attribute than *ObjectType* it may turn out that the measurement and the correct classification of *SpecificPlacement* is much easier to be taken than the measurement and the classification of *ObjectType*. Besides, the inference engine may take advantage of the information of seemingly second-rate attribute *SpecificPlacement* in order to update or even to correct the current value of the fist-rate *ObjectType*.

E. Integration of multiple-source information

Even though the presented concept in itself does not impose any particular requirements on fusion techniques, based on the analysis of gathered information, in the authors' opinion some solutions are preferable over the others. In general, the environment where the measurements are taken is hostile for observation. Utilization of information sources working in three different domains (i.e. magnetic, acoustic, and video) does imply that different factors may obscure readouts from some sensors without affecting the others. Besides, even single source MLO classification is usually made upon very uncertain and incomplete data, which comes from the fact that only a few features of the observed objects may be revealed during observation. This brings to the conclusion that the selected fusion technique should be able to deal with information originated from ontologically different sources with relatively high degree of conflict.

Keeping in mind the above mentioned, the authors have decided to use the *evidential approach* [18], [19], [20], [21], [22]. Particularly, for the purpose of the numerical experiments described in the next section, Dezert-Smarandache Theory (*DSmT*) has been applied. As a natural extension of Dempster-Shafer Theory, *DSmT* has been designed typically for dealing with fusion problems, where the mass referring to conflicting information is relatively high [22]. This seems to be a strong argument for using that framework. Additionally, unlike other approaches *DSmT* distinguishes so called *conditioning rules* (for fusion of uncertain information with certain (e.g confirmed) information) [25], [26] from *combination rules* (for fusion of multiple pieces of uncertain information) [24]. There are over 20 different *rules of combination* and about the same number of *conditioning rules*.

It is worth of notice that *DSmT* as a sort of *evidential approach* does not operate on probability in itself. Instead of probability distribution there are so called *basic belief assignments (bba)* [22], [23], and the decision is made based on the calculated *belief* and *plausibility* functions, which may be regarded as respective substitutes for lower and upper probability in *ULP* model. In order to operate on *bba* a trivial transformation of probabilities to *bba* has been made by mapping them 1 to 1. This operation is completely justified as one realizes that *bba* performs a kind of subjective probability distribution. On the other hand, keeping in mind that in fact the recognition probabilities are just estimates established upon the finite number of trials, the term "subjective probability" seems to be more adequate than simply "probability".

As it was previously postulated by the authors, the fallible reference information should be combined with the rest of the sensor-originated information. For this reason the *classical rule of combination DSmC* has been used. According to this rule all possible intersection of the prior hypotheses are taken into account. The conflicting hypotheses i.e. intrinsically inconsistent e.g. ANCHOR∩BOTTOM are excluded from further considerations.

Table IV performs example evidence table presented to illustrate how the values of the resulting subjective probabilities are calculated.

TABLE IV
EVIDENCE TABLE FOR TWO SENSORS: S_1 AND S_2

S_2 \ S_1	{1,1,10,10} **[0.1]**	{1,2,1,10} **[0.5]**	{1,3,10,1} **[0.3]**	...	{3,1,10,10} **[0.1]**
{1,1,10,10} **[0.1]**	0.01	0.05	0.03	...	0.01
{1,2,1,10} **[0.5]**	0.05	0.25	0.15	...	0.05
{1,3,10,1} **[0.3]**	0.03	0.15	0.09	...	0.03
...	...	...	...	...	...
{3,1,10,10} **[0.1]**	0.01	0.05	0.03	...	0.01

F. Defining prior probabilities

In case of the defined attribute values like: MILCO, MINE, OBSTRUCTOR, etc. the numerical values of the respective recognition probabilities should be defined directly based on the available sensor data, technical specification of the information sources, and knowledge about conditioning of the measurements. In case of undefined attribute values, denoted by UNDEFINED, the subsequent values of probability should be calculated as complements of the sum of all the known values.

It is worth of comment on what basis the above mentioned prior probabilities should be defined is none of the sensor data, technical specification or any further knowledge is existing. In such case it is suggested to acquire such distributions by means of live experiments with usage of fake MLOs which as far as possible behave like their real substitutes.

V. NUMERICAL EXPERIMENTS

In order to verify the proposed solution a number of numerical experiments has been conducted. For this reason an information source simulator had been created in Matlab language. The developed software enabled to simulate upcoming information from the following sources: side sonar, gradiometer, and video camera under good and bad measuring conditions. The particular information sources differed from each other on: values of MLO recognition prior probabilities, and also a number of attributes subject to classification.

A. Experiments with diverse information sources

The first experiment aimed at checking the correctness of the simulated information sources with respect to their distinctive parameters. It was assumed that the measurements would be taken under good conditions i.e. water transparency was sufficient to take full advantage of the video sensor.

In the experiment a mine-like object of type MILCO has been initiated, and then the observation module has been started. The results of the simulation and observation have been registered for each of the sensors. In the following steps the experiment has been repeated with different values of the MLO attributes. The results of the experiment have been presented in Figure 2.

Figure 2 presents a comparison of the recognition probabilities calculated for the three information sources: side sonar, gradiometer and video camera. Purple and red points

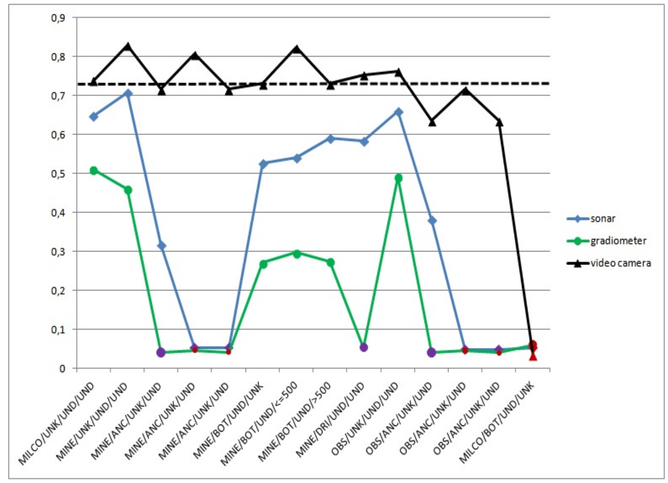

Figure 2. Recognition probabilities estimated for the simulated information sources

denote that for the particular set of the simulated MLO attributes incorrect classifications have been made, i.e. the objects have not been recognized as simulated, wherein purple denotes adequate but imprecise decisions while red denotes incorrect decisions. In such cases the depicted values of recognition probabilities refer to the correct characteristics, however they have not been selected as final decisions. the last simulated MLO for each of the sensor refers to MILCO/BOTTOM/UNDEFINED/UNKNOWN, which is intrinsically inconsistent. This case has been included intentionally for the test purposes, and results in incorrect decisions for each sensor classifier, as expected.

An introductory analysis reveals significant differences in MLO recognition performance for the particular sensors. the magnetic sensor (gradiometer) enabled defining only two of four basic attributes of the observed object (*ObjectType* and *Mass*). Therefore only in six of fourteen cases the simulated MLO was classified correctly by using this sensor. In majority of the rest of the cases (five of eight) the object was recognized incorrectly, and only in three cases the recognition was appropriate, however not precise. the average certainty of the classification by this sensor was $\overline{P}_G$=0.417, which in comparison with average certainty of classification by side sonar ($\overline{P}_S$=0.476) was relatively high.

A detailed analysis of the gradiometer performance shows that the reason for the misclassification (except of inconsistent characteristics object case) is ontologically based, rather than caused by imprecisely defined values of the prior probabilities. Application of that sensor enables only coarse classification of MLO due to the fact that hypotheses referring to more precise classification are not supported by the sensor ontology, and in the consequence, by the measurements.

Application of the side sonar enabled defining three of four MLO attributes (*ObjectType*, *GeneralPlacement*, and *Mass*). Thus the characteristics of the classified bottom mines were retrieved precisely as simulated, since *SpecificPlacement* does not perform a descriptive attribute of the bottom mine. None of the considered case resulted in incorrect classification, but four cases of imprecisely retrieved characteristics, due to the structural similarity of the obstructor and the anchor mine.

Based on the results of the conducted experiments the average certainty of classification by video camera ($\overline{P}_C$=0.728) could be estimated. This value has been calculated as the arithmetic mean of the recognition probability by video camera, obtained for each possible realization of MLO. In the following considerations this value has been effectively utilized in identification criterion.

B. *Experiments with fusion of reliable information*

The second experiment aimed at checking the correctness of the information integration model. Particularly, the emphasis was placed on combination of imagery information from video camera with other sensor information. Similarly, as in the previous experiment, good observation conditions were assumed.

In the experiment a mine-like object of type MILCO has been initiated, and then the observation module has been started. the results of the simulation and observation have been registered for each of the sensors. In the following steps the experiment has been repeated with different values of the MLO attributes. the results of recognition of the simulated objects have been arranged in the following couples of sensors: {acoustic, video}, {magnetic, video}, {acoustic, magnetic}, and the triplet: {acoustic, magnetic, video}. The results of the experiment have been presented in Figure 3.

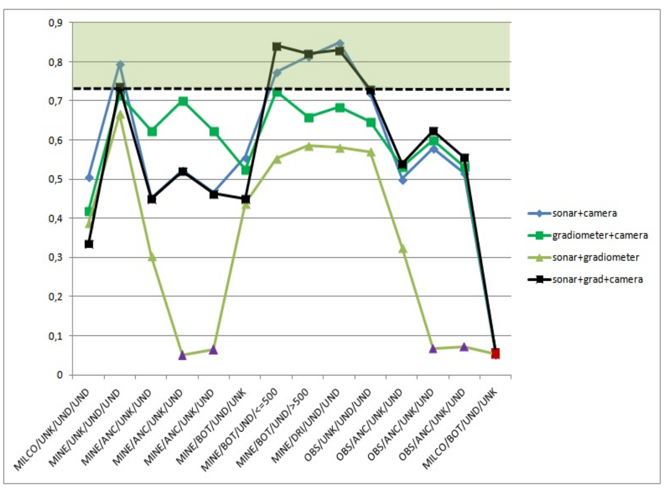

Figure 3. Recognition probabilities estimated for multiple fusion cases - good observation conditions

Figure 2 presents a comparison of the fusion results obtained for the sets of sensors mentioned above. Similarly, as in the previous experiment, red and purple points denote incorrect and imprecise classifications, respectively. Additionally, there has been introduced the mean value of the recognition probability calculated for the video camera, during the first experiment. This value separates the area of precise classification with a high degree of certainty (green colored) from the area, where objects were classified correctly but unsteadily, appropriately but not precise or incorrectly at all. Taking into account the purpose of the experiment the significant sets are those, which contain video camera. the pair {acoustic, magnetic} has been introduced just as a reference for the rest of the results.

An introductory analysis reveals that the qualitative differences among the particular sensors influence significantly on the performance of the fusion. In other words, the more attributes can be defined by using particular sensors, the more adequate the decision is, and the higher the certainty of that decision is. Using the calculated mean value from the first experiment as the threshold for identification, it is easy to notice that only in four cases of observation performed by the side sonar and the video camera the object could be regarded as identified. By using three sensors this number could be raised to five, while in other cases no identifiable object situation has been registered.

Analyzing the mean values of the registered certainties one can notice that the differences among diverse sets are not as explicit as they seemed during the introductory analysis. The calculated mean values were as follows:

– {side sonar, video camera}: $\overline{P}_{S+C}$=0.599,
– {gradiometer, video camera}: $\overline{P}_{G+C}$=0.591,
– {side sonar, gradiometer}: $\overline{P}_{S+G}$=0.426,
– {sonar, gradiometer, video camera}: $\overline{P}_{S+G+C}$=0.586.

This is due to the ontological differences among the sensors. the gradiometer is the sensor of the poorest classification performance, since it is impossible to define *GeneralPlacement* by using it. Coupling this sensor with the video camera or the side sonar will increase significantly the recognition potential, however still it will be poorer than the potential of the individual sonar or video camera ($\overline{P}_G < \overline{P}_{G+C} < \overline{P}_C$). This is due to the fact that the gradiometer does not support any of the hypotheses in which placement of the object (general and specific) is taken into account. but the side sonar and the video camera do. Therefore in case of simulation of any precisely defined object (including defining *GeneralPlacement* and *SpecificPlacement*) degradation of recognition quality for the gradiometer is the biggest. For a comparison, in case of simulation of less precisely defined object the values of of certainty derived from the fusion of the gradiometer with other sensor are relatively high.

Analyzing the results obtained for three sensors it is easy to find cases, where application of the triplet led to better performance than any of the couple. This seems to be quite natural and could be expected in all cases, however did not happen. Moreover, it is possible to find cases, where despite the fact that all sources have interpreted the observed MLO identically, the fusion of two provided better (in terms of recognition probability) results than the fusion of three consistent pieces of information. This phenomenon is also ontologically based. Increase of the sensor number affects the increase of the number of the created secondary hypotheses. the secondary hypotheses (by definition) are not supported directly by the sensor data, however they may be feasible, thus should be verified. During evaluation certain values of probability are assigned to these hypotheses, which results in relatively smaller values of probability assigned to the most probable hypothesis. Certainly, with a sufficient number of sensors this process saturates and no more feasible secondary hypotheses are created. Nevertheless, increasing the sensor number from two to three such phenomenon is still observed. It is worth of notice that in case of precisely defined object MINE/BOTTOM/UNDEFINED/$\leq$500kg the value of recognition probability referring to the sensor triplet was the greatest due to the fact that bottom mine can be precisely described by the gradiometer.

C. *Experiments with fusion of unreliable information*

The third experiment, similarly as the previous one, aimed at checking the correctness of the information integration model. However, this time inconvenient observation conditions were assumed i.e. water transparency was insufficient to take full advantage of the video sensor. the experiment procedure was exactly the same as described in the previous sections. The results of the experiment have been presented in Figure 4.

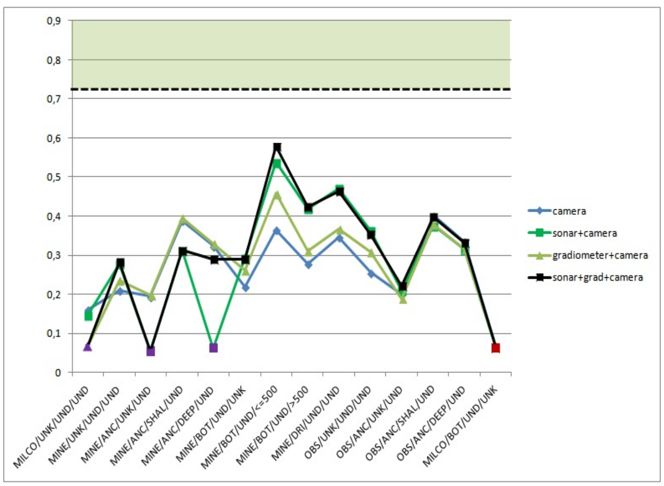

Figure 4. Recognition probabilities estimated for multiple fusion cases - bad observation conditions

Inconvenient observation conditions affect significantly the performance of classification with usage of the video camera, and in the consequence the fusion of information gathered from the camera and other sources. For the purpose of clarification there has been also introduced a plot referring to the recognition probability obtain for the individual video camera. This allows to observe the degradation of recognition quality for the fusion when "the best" source fails or works in extremely inconvenient conditions.

Integration of ontologically different information is not an easy fusion problem. the resulting concept lexicon performs a union of the fusion participant's lexicons. the difficulty arises when the source of reacher lexicon starts to provide information of lower quality than the source of poorer lexicon. An example of such case is examining the mine-like object identification using video camera in inconvenient observation conditions. Simulation of such case has proven a significant degradation of the recognition performance, which caused that in none of the cases MLO could be regarded as identified. The calculated mean value for the video camera was $\overline{P}_C$=0.274, which degraded the quality of the subsequent sensor sets:

- $\{$side sonar, video camera$\}$: $\overline{P}_{S+C}$ =0.322
- $\{$gradiometer, video camera$\}$: $\overline{P}_{G+C}$ =0.289
- $\{$sonar, gradiometer, video camera$\}$: $\overline{P}_{S+G+C}$ =0.327.

Assuming that the lower water transparency had not affected the performances of the rest of the sensors, i.e. the mean values $\overline{P}_S$=0.476 and $\overline{P}_G$=0.417 had not changed, the obtained results may be regarded as moderately satisfactory. Although the above fusion mean values were greater than $\overline{P}_C$ they did not approach significantly the mean value for the side sonar ($\overline{P}_S$), which in such case performed "the best" source.

VI. Mine-like object identification criterion

Based on the results of the conducted numerical experiments the following criterion of MLO identification can be proposed.

$$\forall P(S), \exists P(Thr) = max\{\overline{P}(S)\} : \\ \begin{cases} P(\oplus) > P(Thr) \rightarrow ID \\ P(\oplus) \leq P(Thr) \rightarrow unID \end{cases} \tag{2}$$

For any set of sensors, each of which is described with a recognition probability, the one of the maximum average value of the recognition probability is selected as the reference source, and the maximum average value of probability is selected as the threshold. Thus, for any scenario case where the resulting recognition probability (referring to the final decision) is above the threshold the respective mine-like object is regarded as identified.

VII. Conclusion

The results of the conducted research works have proven that application of a reliable information source of the required classification characteristics, working in ideal conditions, enables achieving high quality decision making in terms of adequacy and precision. However, it is unacceptable to claim that this source provides absolutely infallible information, and the decision made upon it is certain. Additionally, it has been simulated that, in extremely hostile conditions, even the most reliable source of information may supply the system in false information. This, in turn, leads to conclusion that identification of mine-like objects performed in the traditional way is an ill-posed problem, since it is based on the presumption that the reference source provides true information with 100% certainty.

In the authors' opinion information coming from sources hitherto considered as perfect should be integrated with other sensor-originated information. This will increase the quality of the elaborated decision (in terms of adequacy and certainty), and in turn, based on sufficiently high degree of certainty, according to the proposed criterion of identification, the observed object may be identified if that certainty exceeds the preset threshold.

Definition of prior conditional probabilities is another very important problem. In the literature one may find solutions, where conditional probabilities are distinguished from *a priori* probabilities. However, for the purpose of this paper such kind of distinction is not necessary. Therefore these values have been predefined arbitrarily as a presumed product of these two probabilities. It is also the authors' opinion that the precise definition of the prior probabilities is not critical for resolving the considered problem. It will be sufficient if they reveal the true nature of the sources (particularly: classifiers corresponding to these sources). This requirement seems to be very reasonable from the technical point of view, keeping in mind that defining any probability is always approximation due to the finite set of trials. Instead of that, as presented, it is suggested to apply a combination of two approaches: ontological and evidential in order to gain precision of the elaborated results if the source information is reliable (by ontology) and the reasonably adequate approximate result if the source information is unreliable (by Theory of Evidence).

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