2nd IAA Conference on Space Situational Awareness (ICSSA)

Washington, D.C., USA

ON THE USE OF MACHINE LEARNING AND EVIDENCE THEORY TO IMPROVE COLLISION RISK MANAGEMENT

Luis Sánchez[(1)], Massimiliano Vasile[(2)], Edmondo Minisci[(3)]

[(1)] *University of Strathclyde, James Weir Building, 75 Montrose St, G1 1XJ, Glasgow (United Kingdom), luis.sanchez-fdez-mellado@strath.ac.uk*

[(2)] *University of Strathclyde, James Weir Building, 75 Montrose St, G1 1XJ, Glasgow (United Kingdom), massimiliano.vasile@strath.ac.uk*

[(3)] *University of Strathclyde, James Weir Building, 75 Montrose St, G1 1XJ, Glasgow (United Kingdom), edmondo.minisci@strath.ac.uk*

Keywords: Space Traffic Management, Machine Learning, Evidence Theory, Classification, Conjunction Assessment

This paper introduces an Artificial Intelligence-based system to support operators to manage the risk of collision. The system is based on the concepts of Belief and Plausibility coming from Dempster-Shaffer's Evidence Theory applied to collision risk assessment. A revised calculation of the Probability of Collision P_C) is proposed to mitigate the Dilution of Probability that affects the usual definition of this quantity. This phenomenon gives the counterintuitive idea that the lower the quality of the data (or amount of information available to the operators), the smaller the probability of collision. When different sources provide contradictory information, bigger uncertainties are considered which can lead to false confidence in the likelihood of a collision or forces operators to accept very large margins. The method presented here will account for epistemic uncertainty under the assumption of Evidence Theory which leads to the definition of confidence intervals on the probability of a collision. Confidence intervals incorporate the dependency of the probability of collision on the amount and quality of the available information, using the concepts of Belief and Plausibility introduced in Evidence Theory. The result of this revised calculation of the P_C is a more informed decision. At the same time, a lack of information can lead to a higher uncertainty on the decision to be made. Thus the paper will propose a possible approach to make optimal decisions under epistemic uncertainty, considering a given conjunction geometry and the time to the encounter.

In addition to this new approach, an Artificial Intelligence-based system is applied to automatically provide the optimal decisions. A virtual database with a set of encounter geometries and associated uncertainties intervals have been created for training and validating the system. A set of Machine Learning techniques has been used to obtain preliminary results on the potential performance of the system. The system is presented under the form of a classification, where each of the classes for an encounter event is a suggested decision for the operator. Two approaches have been proposed. The first of them uses values of Belief and Plausibility at certain P_C thresholds and the time to the encounter for predicting the class. Very accurate results are provided by the techniques tested. The second approach uses the geometry of the encounter, allowing to skip the time-consuming step of computing Belief and Plausibility. Results suggest that Machine Learning techniques can be applied for obtaining an Artificial Intelligence-based system for supporting operators, although improvements on the methods should be done and a systematic analysis comparing techniques is recommended.

1 Introduction

The continuous increase in space traffic in the last years as well as the expected new mega-constellations and small satellites for the next decades force some changes on Space Traffic Management (STM). The IAA (International Academy of Astronautics) Cosmic Study on Space Traffic Management defined STM as ”the set of technical and regulatory provisions for promoting safe access into outer space, operations in outer space and returns from outer space to Earth free from physical or radio-frequency interference”. An important aspect of STM is conjunction risk assessment. Currently, some level of automation has been implemented by operators for handling the increasing amount of information related to conjunction events. However, those events cataloged as high risk still needs a ”manual” analysis, which is highly time and effort consuming. Moreover, communication between operators rely on emails and low automation is involved. This situation can still be manageable with the current level of space traffic, with something more than 1,000 operative satellites and 20,000 pieces of debris bigger than 10cm [1], but it will be no longer possible in the future [2]. Moreover, adding the new constellations launched for being operative next decade, with thousands of satellites each, the number of conjunction events and the information to be managed by operators are also expected to exponentially increase. In order to keep a safe orbit environment, changes on STM and conjunction risk assessment should be implemented fomenting automation of the system.

Among these changes, the implementation of new techniques for evaluating the information of conjunction event information is a key aspect. Artificial Intelligence (AI) techniques, specifically, Machine Learning (ML) arises as an essential tool due to its ability to handle a huge amount of data. ML methods have been studied in a broad range of engineering fields, including the space sector. Izzo et al. [3] presented a survey with trends on using AI for spacecraft control and guidance. Several examples of the use of AI techniques are presented, highlighting the good performances achieved so far in these areas and suggesting its potential in new domains for automation. Peng and Bai [4, 5] have also used Support Vector Machine (SVM) and Artificial Neural Networks (ANN) for reducing orbital propagating errors and improving orbit determination. However, the use of AI for collision risk assessment is less extended. It is worth mentioning two works: Vasile et al. [6] and Sanchez et al. [7]. In the former, a system for supporting the planning and implementation of collision avoidance maneuvers (CAM) is presented using ML (Elastic Nets) and a maneuvers dataset, with special attention on the future consequences on the global space environment. The latter shows the viability of using ANN for predicting conjunction events. An ANN model using exclusively a pair of satellites' Keplerian parameters at a certain epoch is shown to be able to predict the orbit along with a certain interval of time for which the system was trained. The prediction of the equinoctial parameters compared with the results from a high fidelity propagator are accurate enough to determine the occurrence of a potential conjunction event based on the value of the B-parameter between the two orbits considered.

Based on the results from [7], this paper presents the next logical step regarding the build of an autonomous AI-based system able to give support on every step of the STM process: the classification of conjunction events for the decision making process. Since the ANN model cited before provides a prediction of potential conjunctions, the model presented here aims to focus on those events in order to classify them based on a series of factors: time to the event, uncertainty associated to it and confidence associated with those uncertainties. Information provided by the system can help operators on the decision making and will eventually give the inputs for an autonomous decision-making system for CAM and will be an essential part for an AI-based agent for automatic STM.

The contribution of the paper is that classification is done based on the confidence associated with the evidence, avoiding the problem of probability of dilution associated with the probability of collision when information comes from contradictory sources. While probability of collision is a widely used metric for risk assessment [8, 9, 10, 11], there are also concerns that it lead to false confidence decisions due to dilution of probability [12, 13]. The root of this problem can be found in the fact that epistemic uncertainty is treated as an aleatory variable. Here, we proposed accounting for epistemic uncertainty on the risk assessment process through the use of Dempster-Shafer Evidence Theory (DST) [14], deepening on the proposal made by Sanchez et al. [7]

The rest of the paper is structured as follows. In Section 2, a brief explanation of dilution of probability and its relation with the epistemic uncertainty is presented, as well as an introduction to Evidence Theory and its application on conjunction risk assessment. Section 3 presents a classification of risk events taking into account epistemic uncertainty under DST and compare it with current ways for classifying events. In Section 4 ,the AI-based classification model is presented, as long as the databases created for training it and the results of its performances. Finally, Section 5 summarize the main conclusion of the paper and suggest future research.

2 Evidence Theory on collision risk assessment

2.1 Dilution of probability

Dilution of probability is a problem that affects the computation of the Probability of Collision, P_C, when uncertainty is increased.

The Probability of Collision is a common metric in conjunction risk assessment. Usually it is computed under the assumption of a short term encounter [8, 9, 10, 11]:

- Relative motion between objects is assumed rectilinear.
- Uncertainty on position is considered to follow a Gaussian distribution with zero-mean and uncorrelated between bodies.
- Covariances in velocity are assumed zero.
- Objects are modeled as hard spheres.

P_C is computed by integrating over the close region defined by the Hard Body Radius, HBR (sphere enveloping the two objects) the combined uncertainty ellipsoid centered on one of the bodies and projected on the impact plane: Equation 1. More details on the derivation of this equation can be found in [11].

$$P_C = \frac{1}{2\pi\sigma_x\sigma_y} \int\limits_{\mathcal{B}((0,0),R)} exp\left(-\frac{1}{2}\left(\frac{(x-\mu_x)^2}{\sigma_x^2} + \frac{(y-\mu_y)^2}{\sigma_y^2}\right)\right) dxdy \tag{1}$$

However, this formulation leads to the well known paradoxical phenomenon of dilution of probability [12]: worsen the data quality (translated in bigger uncertainties, σ) seem to give lower risk when uncertainty is greater than a certain value (Figure 3. This idea is not only counter-intuitive but also leads to false confidence that an event that is safe when actually it can be not safe. [13]

In [13], it is shown that the mathematics supporting the model are straightforward, but not the model of uncertainty. In fact, the root of the problem is that uncertainty is treated as purely aleatory, and bigger uncertainties translate into increases of the standard deviation 2. However, this is just true when dynamics and sensors are perfectly known and uncertainty comes from the process itself. However, when data quality is due to the lack of knowledge on the position or velocity of the satellite due to not perfect models or sensors, the conclusion of the reasoning is that the higher ignorance, the safer the situation.

What it is proposed here is to include the lack of knowledge on the computation of the P_C, assuming that uncertainty in the state and the dynamics is nor only aleatory, but also epistemic. When recalculating the probability of collision under this assumption, its value is related to plausibility and belief on the quality of the data and the actual information available by the operator. The approach taken here for including epistemic uncertainty continues the worked developed in [7] using Dempster-Shafer Evidence Theory.

2.2 Evidence Theory

As mentioned, a fundamental aspect of the approach proposed for computing risk of collision is assuming that uncertainty has an epistemic component due to lack of knowledge. Dempster-Shafer Evidence Theory is a technique able to handle this uncertainty. The core of the theory is that a degree of confidence in a realization can be associated with an event, without an exact known on its probability, assuming sources of information are independent and uncertainties uncorrelated.

Given an event space, the set Θ of all the mutually exclusive and collectively exhaustive elementary events (or hypotheses) $\Theta = \{\theta_1, \theta_2, ..., \theta_i, ..., \theta_{|\Theta|}\}$ is considered. The different available sources of evidence are treated independently in this paper.

The collection of all non empty subsets of Θ is the Power Set $2^\Theta = (\Theta, \cup)$. One can now assign a probability mass, called basic probability assignment (bpa), to the elements of 2^Θ. Each element of 2^Θ with a non-zero bpa is called a *Focal Element* (FE) and is represented with the symbol γ in the following. In this work, The pair $\langle \Gamma, bpa_\Gamma \rangle$ - where $\Gamma \ni \gamma$ and $bpa_\Gamma \ni bpa_\gamma$ - is called the *Body of Evidence*and the power set $U = 2^\Theta$ the *Uncertain Space*. It is possible now to define the performance index of the system to be analysed as:

$$f(\mathbf{u}) : U \subseteq R^m \to R \tag{2}$$

where U is the event space for the uncertain parameters **u**, with dimension m.

The influence of epistemic uncertainty is quantify by Plausibility and Belief functions. If set Ω show the amount of evidence associated to an event:

$$\Omega = \{\mathbf{u} \in U | f(\mathbf{d}, \mathbf{u}) \in \Phi\} \tag{3}$$

then, the Belief and Plausibility functions are defined as:

$$Bel(\Omega) = \sum_{\gamma_i \subset \Omega, \gamma_i \in U} bpa(\gamma_i), \tag{4}$$

$$Pl(\Omega) = \sum_{\gamma_i \cap \Omega \neq \emptyset, \gamma_i \in U} bpa(\gamma_i). \tag{5}$$

On the one hand, belief accounts for the *bpa* of the FEs totally included in Ω, what means that evidence completely supports a given proposition, i.e. amount of positive support. On the other, Plausibility accounts for *bpa* of the FEs partially included in Ω. It is the lack of support against the proposition, or what it is the same, evidence does not completely support the propositions, but neither completely support the fact that it is false.

2.3 New Formulation of the Risk of Collision

As explained in [7], Evidence Theory can be used for collision assessment for accounting for epistemic uncertainty. Given a conjunction event, information about the position and velocity of the bodies involved are put together, as well as their uncertainties. This information can come from one or more sources of information (like on-board sensors, ground tracking system, propagation models...). These sources can give coherent or contradictory information. From a probabilistic point of view, the way for accounting for all this information, even when there is conflict among them, it is by using greater uncertainties, in order to include all of them. This conflict among sources (root in epistemic uncertainty) leads to greater distributions when is treated as aleatory uncertainties, causing the dilution of probability. Since Probability of Collision is computed using that combine ellipsoid, the bigger it is, the higher the dilution of probability if sources provide not similar information.

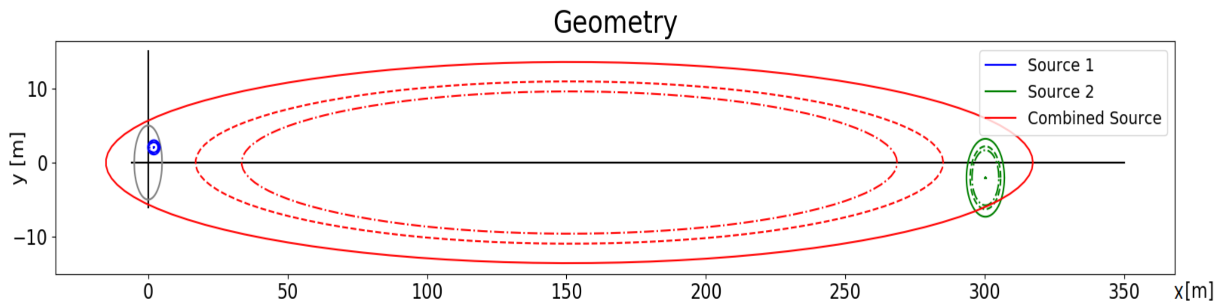

Figure 1: Source 1 (blue), source 1(green) and combined sources (red), with the corresponding distributions projected on collision plane.

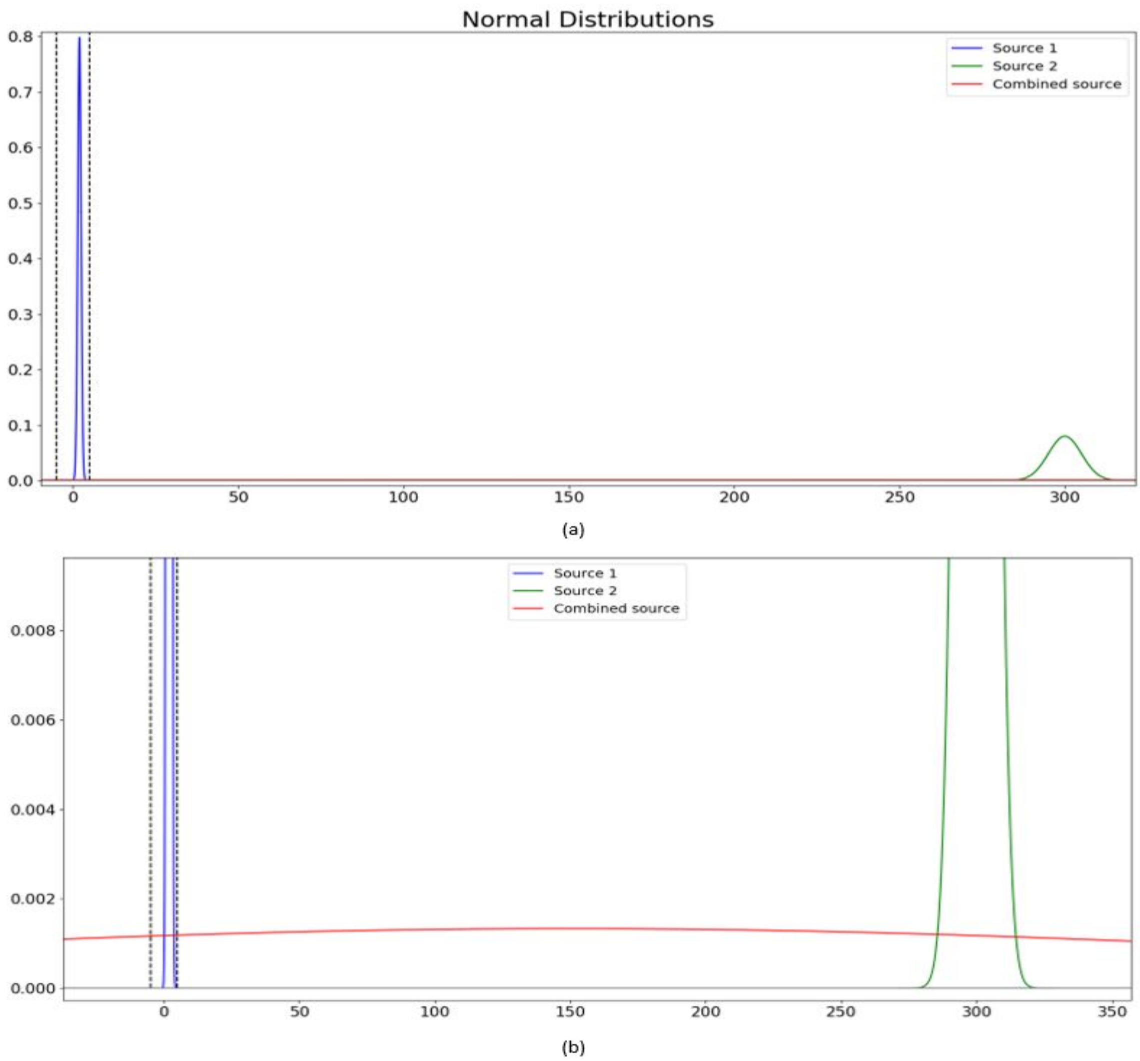

Figure 2: 1D Normal distribution simplification of the above cases. It can be seen how the distribution flattened (red) due to the combination of two narrow distributions (blue and green). Up: overview; low: detail.

However, using Evidence Theory allows obtaining more meaningful information from those sources, being possible accounting for epistemic information. Using this method, confidence associated with the sources can be used to handle conflict among the provided information. To do so, Belief and Plausibility of an event are computed, given the information is provided in the form of intervals. Each of those intervals can be though as a family of normal distributions whose parameters are enclosed by the range of values included on the intervals. In this paper, the assumption of Normal Distributions for computing P_C is still assumed, so the intervals are given for μ and σ in both directions of the collision plane.

When information among sources is contradictory, instead of taking bigger distributions to compensate for this lack of knowledge, Belief and Plausibility will provide information about the confidence in the values of probability of collision.

Figure 1 presents an example for showing these differences. In this situation, two sources of information are considered. One of those sources suggests a risk event is likely (Blue Source), while the other one suggests the opposite (Green Source), both of them with low uncertainties in the position. Such an scenario has implication from the point of view of an operator. Regarding the contradictory information, operators can decide to use one of the sources because is considered more reliable. Taking information only from the Blue Source, the low miss distance and low uncertainty will give a high probability of collision. Exactly the opposite can be said taking the Green Source. However, it implies one of the sources has to be selected while the other completely discarded. If both sources of information are wanted to be considered, the probabilistic strategy will use a combination of both families of distribution (red ellipse).

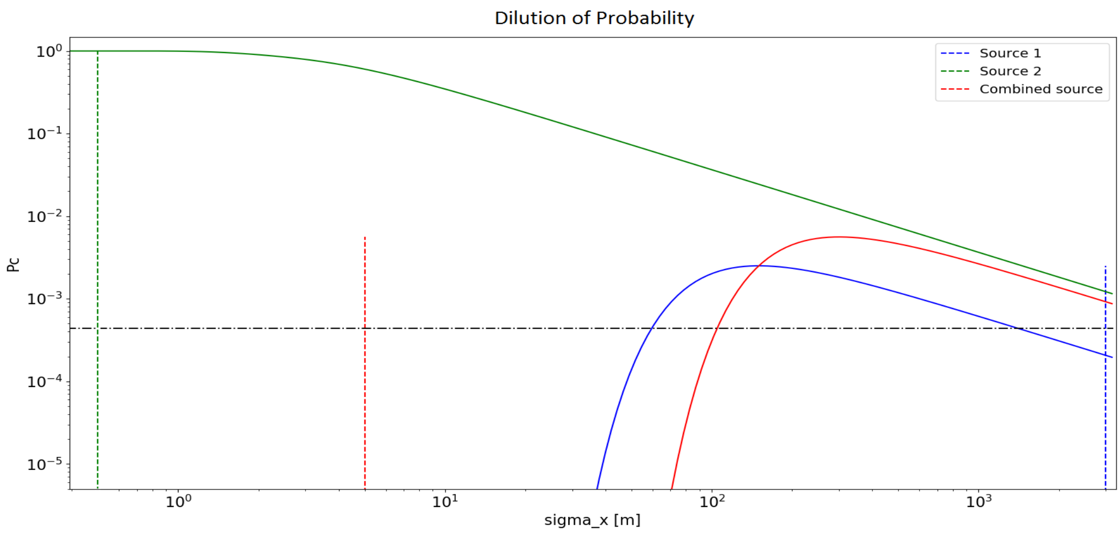

Figure 3: Dilution of probability due to combination of sources (red). When both sources are considered separately (blue and green), they do not fall in the dilution region.

As can be seen, while both sources individually present relative small values of uncertainty, the combination of both for the probabilistic computation of probability of collision is much bigger, which leads to a dilution of probability. Figure 2 shows how the distribution, assumed Normal and simplify into 1D, changes from the individual cases to the combine one, and how it affects the area under the curves inside the integration region. In this situation, the operators may compute a low probability of collision, that does not actually come from the information provided, but for the lack of information related to the conflict on the sources, what can leads to a false confidence situation if the source suggesting a collision was actually the right one. Figure 3 shows how the probability of collision vs standard deviation curves change from considering each of the sources separately to combine under one distribution enclosing both. It can be seen how in the latest case, the value of probability falls in the dilution region. In fact, if the black dash line represents a threshold for classifying events, this event wouldn't be cataloged as high risk, even if it could not be true. More detail about classification event will be provided in Section 3.

On the other hand, Evidence Theory uses information from both sources separately, instead of combining them. If both sources are taking into account assuming a similar level of confidence, Belief and Plausibility curves like those in Figure 4 are obtained. Different information can be taken from them: regarding Figure 4(a), evidences suggest that a collision can occur (as expected, taking into account Blue Source's information), but it also indicates how much confidence the operator can put on that proposition, since Belief is far from 1 and Plausibility still is high for values of P_C greater than 0.1. Even more important, Evidence Theory is able to account for different sources of information avoiding dilution of probability. While the probabilistic approach combined both distributions into a bigger one which leads to small values of P_C but with high uncertainties, Evidence Theory indicates how much the operator can be confident in his/her decision. Which decision the operator should take in such a situation is something to be discussed in the next Section.

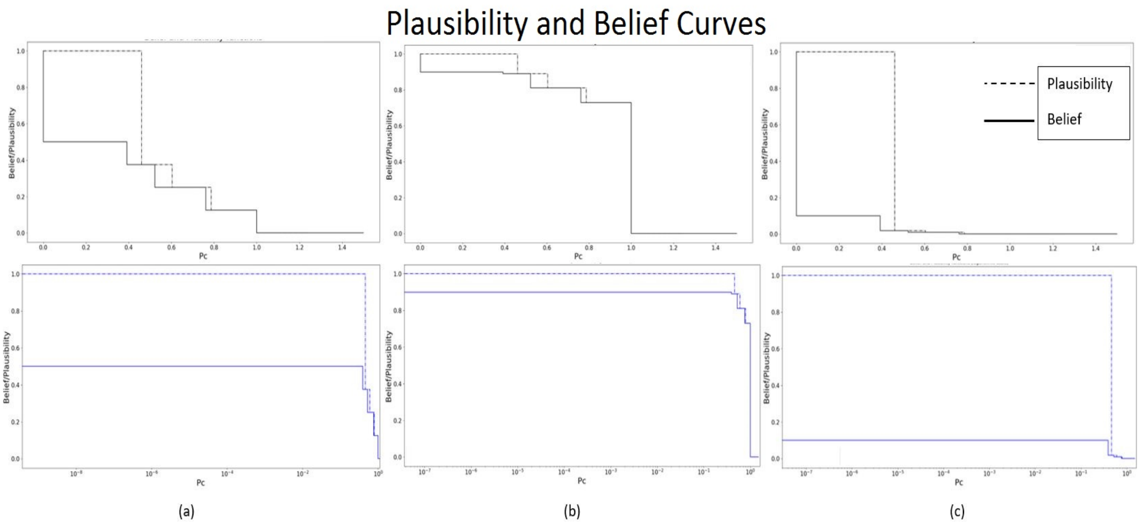

Figure 4: Belief and Plausibility curves (natural and logarithmic scale) for the geometry given in Figure 1. (a) Both sources equally reliable. (b) Source 1 more reliable. (c) Source 2 more reliable.

If, in addition, more confidence is put on one of the sources, Evidence Theory can provide more information. Assuming Source Blue is more reliable curves like those in Figure 4(b) are obtained, which gives high support to the idea of a collision to happen since not only Plausibility but also Belief is high, still considering both sources of information. On the other hand, if more emphasis is put on the Green Source, obtaining a set of curves like those in Figure 4(c). It says that the operator can be more confidence in the fact a collision is not going to occur since Belief presents a really low value. The important point, however, is that this high confidence in a collision not to happen does not come from a dilution of the probability but from the evidence provided by the sources and the reliability on them.

When the information from the sources is more coherent among them, for example if both sources suggest a collision was likely and presented low uncertainty, the combine ellipsoid would not be very different from the original ones, and values of P_C will be similar and they were not expected to fall in the dilution region. Using Evidence Theory, the results would suggest high confidence on high values of probability of collision. Something similar would occur if those small ellipsoids related with low uncertainty were presented a high value of miss distance: the combine ellipsoid would be again similar to the original ones and would suggest a collision is unlikely, same as using Evidence Theory: small confidence to high values of P_C.

Nevertheless, there are still some limitations to this method. First of all, only Normal Distributions are considered for the uncertainty in position, so only intervals for the values of their means values and standard deviations are considered. Moreover, for simplification on the computations, those uncertainties are assumed to have the same orientations on the space (i.e. semimajor axis of the projected ellipsoids on the B-plane have same directions). Improvement can be done considering wider distributions of uncertainties, but especially, using a wider set of distribution families. However, these situations lead to a bigger set variables (and corresponding intervals) for been taken into account. Linked to these limitations, Equation 1 is still used for obtaining the values of Probability of Collision, later used for building the Belief and Plausibility curves. This fact leads to situations where, if the values of the uncertainties provide in all the intervals are high enough to fall in the dilution region, the conclusions using Evidence Theory still will be a high confidence that high values of P_C are not going to happen.

3 Conjunction event classificator

The application of Evidence Theory for collision risk assessment presented in the previous Section can be completed with a classification of conjunction events. This classification would be based on the confidence that P_C is higher than certain values. In this section, these classification methods will be explained after some current criteria are presented.

3.1 Current classification criteria

Currently, some operators, including the CARA team of NASA or the Space Debris Office (SDO) of ESA, rank the potential conjunction events depending on the value of the probability of collision [15, 16]. Each operator follows its own method and criterion, but all of them are based on the computation of the epistemic probability of collision of an event using Equation 1, using the information provided by different sensors or catalogs, and tend to be sensitive to small probabilities. The uncertainty in relative position and velocity associated with these sources or with the models used for obit determination is treated as purely aleatory, regardless if some have an epistemic origin. For this reason, these criteria can suffer from dilution of probability.

The model used by the CARA team of NASA is based on two values of the P_C used as thresholds to compare with the computed value of probability and classify the event. Those values are computed in order to obtain a specific frequentist error rates by using past data of other events as a reference population. More details of how these thresholds are obtained can be found on [15]. The values for the lower and upper thresholds are set as 10^{-7} and 4.4 x 10^{-4}, respectively. Events with a P_C greater 10^{-7} would be monitor and events whose epistemic probability of collision is higher than 4.4 x 10^{-4} would be treated as high risk.

The ESA's Space Debris Office follows a different but similar strategy. In this case, they use only a single threshold that is selected based on a compromise between the assumed and reduced risks of performing a CAM, trying to minimize the number of maneuvers expected by the satellite during its lifetime. Although each mission has its own threshold, the value obtained is usually close to 10^{-6} one day before the event for a reduction on the risk of 90% (reduction compared to the risk assumed of not taking any action). [16]

Both models are based on the computation of the probability of collision assuming aleatory uncertainty and the way they deal with dilution is pursuing low thresholds. However, low thresholds do not ensure being free of false confidence unless good quality data are available [13]. However, if information comes for conflict sources, as in the example of Section 2, it is likely them to fall in the dilution region. Both models contemplate the possibility of collecting better quality data to refine their knowledge, but although they come from coherent sources and are good quality, false confidence would be present.

To try to overcome some of this limitation, the classification proposed below uses the Evidence Theory concept applied to conjunction risk assessment.

3.2 Evidence Theory based classification

Unlike the previous criteria that use the face value of P_C as a metric for decision making, the model presented here uses the concepts of Belief and Plausibility applied to conjunction risk assessment, as explained in Section 2, accounting for epistemic uncertainty. The uncertainty associated with the position of the bodies involved in an event is not used to compute P_C, but to obtain the Belief and Plausibility curves of the probability being greater than a given value, supported by the evidence. In the end, it is the confidence the evidence gives to the fact that a an events has a probability of collision high or low what drives the decision.

The idea of this classification is to avoid situations like the one presented before when contradictory information is provided. Depending on the levels of reliability on the sources as well as the values levels of confidence set for this method, the operator can take a decision not biased by dilution of probability.

The new classification proposed here uses five parameters to differentiate the classes: two threshold for the time to the encounter, another two for the probability of collision for evaluating the values of Belief and Plausibility and a last one for discern between what is considered a high or low confidences, or what it is the same, high and low values of Belief and Plausibility. The class will be defined regarding the value of Belief and Plausibility at those risk thresholds as well as time to the encounter, finding five different situation or classes:

1. Perform CAM. An event happening close in time and presenting high support on high values of probability of collision.
2. Prepare CAM. An event with support on high values probability of collision, but happening not as close in time.
3. Follow the event. An event not close in time with reasonable confidence that can be a high risk event if more data are acquired or an event with high lack of evidences against high values of probability of collision.
4. Low risk event. An event not close in time with high confidence that the event does not present a high value of probability of collision.
5. No perform CAM. An event close in time that presents high confidence that the value of probability of collision is not high or presenting low evidences against P_C being high.

In Table 1, a summary of the different combination of times and values of belief and plausibility are presented with the corresponding class.

Situations where the time to the encounter is higher than the upper threshold, events are classified as 2, 3 and 4 appear. These classes do not suggest a definite decision or suggest the acquisition of better data. They are examples when the gap between belief and plausibility is not small. In such a situation, a low belief means that evidence does not support the fat that P_C is high. However, a high Plausibility means at the same time that high values of P_C cannot be discarded from the evidence. When the events present a short time window, a decision has to be made, that is the reason why events with times below the lowest threshold are classified just as 1 or 5. Since there is no more

Table 1: Classification of events.

Time to conjunction	Belief at high P_C	Plausibility at high P_C	Belief at low P_C	Plausibility at low P_C	Class
Low	High	High	High	High	1
Low	Low	High	High	High	1
Low	Low	Low	High	High	5
Low	Low	High	Low	High	1
Low	Low	Low	Low	High	5
Low	Low	Low	Low	Low	5
Med	High	High	High	High	1
Med	Low	High	High	High	2
Med	Low	Low	High	High	3
Med	Low	High	Low	High	3
Med	Low	Low	Low	High	4
Med	Low	Low	Low	Low	5
High	High	High	High	High	2
High	Low	High	High	High	2
High	Low	Low	High	High	3
High	Low	High	Low	High	3
High	Low	Low	Low	High	4
High	Low	Low	Low	Low	4

time to obtain more data, those cases mentioned before as 3 or 4, now require an action. Whether it is a maneuver or not depends on how conservative the operators want to be, given the confidence they have on the decision.

Coming back to the example of the previous Section whose geometry can be found in Figure 1, the difference of classification depending on the criteria can be illustrated. This geometry assumes two accurate sources, we can assume they provide the intervals of Table 2.

Table 2: Intervals of sources for example in Figure 1

Source	μ_x [m]	μ_y [m]	σ_x [m]	σ_x [m]
Blue source	[1.8 - 2.1]	[1.9 - 2.2]	[0.5 - 0.6]	[0.1 - 0.25]
Green source	[290 - 310]	[(-2.1) - (-1.8)]	[5 - 6]	[2.8 - 3.2]

Taking the mean values of each interval, assuming Normal Distribution and using Equation 1, the P_C provide for each source independently would be 0.99 and 10^{-55}, respectively. Both methods, the CARA team and the SDO, would catalog the event as High Risk and Low Risk if considering only the Blue Source or the Green Source, respectively. However, assuming a the combine ellipsoid (in red) has the following mean values for its parameters: $\mu_x = 150m$, $\mu_y = 0m$, $\sigma_x = 3000m$, $\sigma_y = 20m$, the probability of collision would be 2.4x10^{-4}, been classified as High Risk event by the SDO, but not by the CARA team.

By contrast, the classification proposed here, assuming both sources are equally distributed and using the thresholds included in Table 4, the event would be classified as Class 1 or Class 2, depending on the time to the encounter, meaning operator should perform or prepare a CAM being confidence that evidence supports this decision. However, assuming one of the sources is more reliable than the other, different classes would be obtained. For example, assuming more reliability of Green Source, classes 1 and 3 would be suggested by the system (Figure 5), while considering Blue Source more reliable, again class 1 and 2 would be the output. The important part of this classification is that any of the decisions associated with the classes can be taken with the confidence that they are based on the evidence.

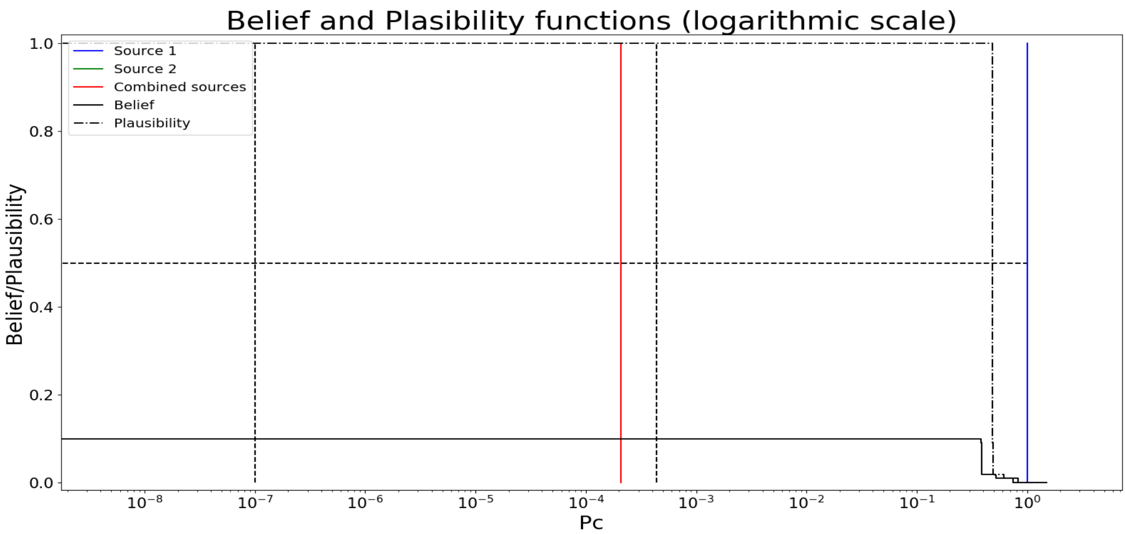

Figure 5: Belief and Plausibility Equally, assuming Source Green is more reliable, of example in Figure 1 compared with values of P_C of Source Blue, Source Green and Combined Source (red) using Equation 1. Black dash lines: P_C and confidence thresholds.

4 AI-based classification system

Based on the idea of using Evidence Theory for collision risk assessment, one of the contributions of this paper is to present the new method for event classification accounting for epistemic uncertainty explained before. The other major contribution of the paper is introduced in this Section: implementing this method into an AI-based classification system. Regarding the increasing orbital population expected for the next years, growth in the number of conjunction events is expected as well as in the amount of information that operators have to deal with. Current procedures for dealing with conjunction events, and especially with high risk events cannot be longer used since the high workload and the time they require to the operators. In this sense, automatizing not only the alerts but also the events classification and the actions to be implemented is an issue to be addressed. AI systems can be a good tool for this task, regarding their ability for learning from data, to deal with a great amount of information and for making predictions in much shorter periods of time than classical models. As a strategy to built an AI-agent for Space Traffic Management, different pieces have to be put together, and one of them is this system for classifying and supporting decision-makers.

AI techniques have proved their ability for classification tasks. Some of them are tested in this paper for predicting the best action, based on the classification presented in the previous Section, using the Belief and Plausibility curves associated with an event.

Two classification systems have been built. Both of them provide the class or recommended action to take based on the classification criteria exposed in the previous Section. The difference among both systems are the inputs provided: one of the systems uses the same values used for making the classification: time to encounter and values of Belief and Plausibility at the lower and upper P_C thresholds. The second system goes a step blackguards on the process and uses the intervals that define the encounter geometry.

In this way, it is possible to skip the computation of the Belief and Plausibility curves, which represents the most time-consuming step.

Both methods use for training and validating a virtual database of geometries which is explained below.

4.1 Databases

Due to the lack of information regarding Belief and Plausibility associated with real collision events or intervals from which uncertainties have been built, a database of events has been created based on a set of artificial encounter geometries. This database has been used for both, training and validating the different models.

The first classification model takes as inputs the same five parameters mentioned in Section 3 for classifying the events: time to the encounter and values of Belief and Plausibility at the lower and upper thresholds. The seconds model uses directly the intervals provided by the sources and the time to the encounter. Therefore, to obtain the databases with the features needed for both models and the corresponding class of the events, a set of encounter geometries have been considered.

A geometry is defined by the Hard Body Radius (HBR) of the combine objects (for this paper, a fixed value of 5m has been considered for the HBR) and the interval or intervals provided by the sources of both components of the miss distance into the B-plane and the two components of position uncertainty (note that semimajor axis of the projected ellipses are assumed to be parallel among ellipses and to the reference axis on the plane): the mean values (μ_x and μ_y) and standard deviations (σ_x and σ_y) for the corresponding families of Normal Distributions. Different sets of geometries varying the size of the intervals and the lower and upper values have been created. In this way, different scenarios wanted to be represented: small miss distances with small uncertainties, small miss distances with bigger uncertainties, conflict intervals like those presented in 2, situations with low and high uncertainties depending on the sources... A list with the scenarios and the upper and lower values of the intervals for each variable is presented in Table 3.

Table 3: Set of geometries for creating the databases.

Geometry	μ_x [m]	μ_y [m]	σ_x [m]	σ_y [m]
Geometry 1	[0-50]	[0-25]	[0.01-1]	[0.1,1]
Geometry 2	[0-50]	[0-25]	[0.1-10]	[0.1,3]
Geometry 3	[20-50]	[15-25]	[6-10]	[2-3]
Geometry 4	[20-50]	[15-25]	[0.01-1]	[0.1-1]
Geometry 5	[20-50]	[15-25]	[0.1-10]	[0.1-3]
Geometry 6	[20-50]	[15-25]	[0.01-0.2]	[0.1-0.5]
Geometry 7	[0-15]	[0-10]	[0.01-1]	[0.1-1]
Geometry 8	[0-15]	[0-10]	[0.1-10]	[0.1-3]
Geometry 9	[0-15]	[0-10]	[0.01-0.2]	[0.1-0.5]
Geometry 10	[0-15]	[0-10]	[7-10]	[6-8]
Geometry 11	[0-5]	[0-3]	[7-10]	[6-8]
Geometry 12	[0-5]	[0-3]	[0.1-10]	[0.1-3]
Geometry 13	[0-5]	[0-3]	[0.01-0.2]	[0.1-0.5]

For each geometry, 1000 events have been created, each of them presenting 1 or 2 intervals per variable. For the first classification system, having the geometries, Plausibility and Belief curves have been created as explained in Section 2. Once they are obtained, their values at the P_C thresholds are recorded. Finally, the events have been associated a time. This time represents the time in advance the collision is detected. For having a wider casuistic, three samples have been created from each event. Each of these samples has been associated a time for each of the time slots used for classification. Finally, the corresponding class is computed for each sample. The database has been divided into two parts in a proportion of 80-20% for training and testing respectively. The values for the threshold used in this paper can be shown in Table 4. In total, 39,000 samples (13 geometries x 1,000 events per geometry x 3 times) have been created.

For the second classification system, each event has been created using the upper and lower values of each interval for each variable. Each of these events has been associated the same three times mentioned before and the corresponding class has been included. Different databases have been created, regarding the number of intervals per sample. According to this, samples coming from geometries with one intervals contains 9 features (upper and lower values of intervals for the fours variables plus the time) and one class, samples created from geometries with two intervals contains 17 features (upper and lower values of intervals for the fours variables for the two sources plus the time) and one class, and so on.

Table 4: Thresholds used for classifying events.

Variable	**Value**
Upper Time Threshold	4 days
Lower Time Threshold	2 days
Upper Time P_C	4.4x10^{-4}
Upper Time P_C	10^{-7}
Belief/Plausibility Threshold	0.5

4.2 ML Models

Different supervised ML techniques have been tested to study the possibility of predicting the proposed classes given the geometry of a close encounter. Bearing in mind the main objective of this analysis is proving the capacity of an AI-based system of capturing this relation, neither an exhaustive study of methods and their parameters neither a detailed comparison among methods have been performed, having left for future researches. The techniques tested in the paper have been: Artificial Neural Networks (ANN), Random Forest (RF) and K-Nearest Neighbours (KNN).

Artificial Neural Networks consist of a series of interconnected nodes organized in layers that moved information from the input layer to the output. Each node on the layer has a weight that is updated for minimizing a loss function that compares the value predicted by the network with the real one by a stochastic gradient descent (SGD) process that is performed from the last layer to the first one. [17]

The ANNs trained in this paper contains only one hidden layer, apart from the input and output layers. Since it is a classification problem, there are five outputs, one per class, that can obtain values between 0 and 1. Ideally, when inputs of a class *k* are provided, all nodes in the output layer should take value 0 but node *k* that should take value 1. The only hyperparameter modified in this study has been the number of neurons on the hidden layer. Each neuron posses a hyperbolic tangent activation function, the optimizer used has been the Levenberg-Marquardt method and the loss function the cross-entropy. Each configuration has been trained iteratively with different initialization of parameters. The model providing the lower value of loss function has been selected. The model has been implemented using the MATLAB *Deep Learning* Toolbox. [18]

Random Forest is an ensemble method that combined several independent Decision Trees during the training step, feeding each of them with different subsets of the training set. The final class predicted is selected as the mode of the outputs of every single tree. Random Forests overcome the overfitting problem usually faced by Decision Trees. [19]

In this paper, a few RFs configurations have been trained, modifying some of its hyperparameters among some values: number of trees in the forest, maximum depth of the tree, the minimum number of samples required to be at a leaf node, the minimum number of samples to split a node... All the other parameters have remained as the default values selected by the ”Scikit” library of Python [20]. The combination with the best accuracy over all the samples (correct predicted samples over the total number of samples) has been selected.

K-Nearest Neighbours algorithm predicts the output of a given sample comparing its proximity with the training samples. Once an input vector is given, the closeness to the other points is computed (it can be Euclidean distance or any other metric) and the K nearest points are selected. The class of the sample is selected as the mode of those values. The selection of the optimum K depends on the problem. [21]

In this paper, some KNN models have been trained, changing also some of the hyperparameters among some values: number of neighbors K, weight function, leaf size when used in some of the inner algorithms... All the other hyperparameters have been lefts as the default values set by the ”Scikit” library of Python [22]. The model with better results has been saved.

Accuracy of each method as well as precision and recall for each of the class over the test dataset has been computed for each method and each system. The results are presented in the next section.

4.3 Results

4.3.1 Classification system 1

As explained before, this model uses 5 inputs for predicting the class of a certain event. These five inputs are: time to the encounter and Belief and Plausibility values at the upper and lower thresholds.

As shown below, this method has the main advantage of presenting a very good accuracy on the prediction of classes for a given event even if just simple models have been tested. Since it uses as inputs the same parameters used for classifying events, it seems not to be a difficult task to find the underneath relation between inputs and outputs. In Table 5, precision and accuracy for each method over all the samples and split by classes are shown.

Table 5: Results of prediction of different model for System 1. All values are in percentage.

Model	**Total** Accuracy	**Class 1** Prec. - Rec.	**Class 2** Prec. - Rec.	**Class 3** Prec. - Rec.	**Class 4** Prec. - Rec.	**Class 5** Prec. - Rec.
ANN	99.8	97.5 - 96.7	81.8 - 90.0	98.6 - 98.7	99.9 - 99.9	100.0 - 99.9
RF	**100.0**	**100.0 - 100.0**	**100.0 - 100.0**	**100.0 - 100.0**	**100.0 - 100.0**	**100.0 - 100.0**
KNN	99.6	97.1 - 95.7	94.7 - 90.0	94.9 - 95.53	99.7 - 99.7	99.9 - 99.9

Results from Table 5 suggest that the best method among those tested in this work is Random Forest, although all methods provide promising results, both in the overall score and by classes. Nevertheless, the results of this comparative should be seen simply as a guide since, as has been noted previously, the models trained for the different techniques are naive ones. The interesting information that can be obtained from this table, however, is the possibility of obtaining very good predictions using ML techniques for classify conjunction events. It is worth mentioning that a simple Random Forest model is able to predict classes with an accuracy of 100% over the more than 3,000 samples using on the validation set.

However, despite the good results this system presents, it still needs the values of Plausibility and Belief. This a time-consuming process, especially if several intervals are considered. In order to avoid this process, another classification system has been tested.

4.3.2 Classification system 2

The main advantage of this system compared to the previous one is that the computation of Belief and Plausibility is not needed since it uses as inputs the values of the intervals provided by the sources, as well as the time to the encounter. Table 6 presents the results using different ML techniques.

Table 6: Results of prediction of different model for System 2. All values are in percentage. The rows for each method represent the values over samples with 1 or 2 intervals, respectively.

Model	**Total** Accuracy	**Class 1** Prec. - Rec.	**Class 2** Prec. - Rec.	**Class 3** Prec. - Rec.	**Class 4** Prec. - Rec.	**Class 5** Prec. - Rec.
ANN	**95.8**	**82.5 - 86.7**	**72.7 - 53.3**	**86.9 - 48.2**	**98.0 - 94.2**	**95.3 - 99.4**
	94.1	**73.9 - 55.7**	**NaN - 0.0**	**60.2 - 41.2**	**97.2 - 92.6**	**94.0 - 98.7**
RF	95.0	90.6 - 88.3	0.0 - 0.0	35.4 - 22.1	91.9 - 86.2	96.9 - 99.9
	93.7	67.3 - 54.1	0.0 - 0.0	22.2 - 13.3	90.5 - 84.5	96.3 - 99.7
KNN	90.9	53.0 - 51.7	0.0 - 0.0	33.7 - 22.1	82.4 - 78.8	95.1 - 97.3
	83.6	35.4 - 27.9	0.0 - 0.0	34.1 - 26.7	57.4 - 46.6	90.6 - 96.0

It is clear from Table 6 that results from this system using similar models are worse than from the previous system. However, currently, this is not the point of using this approach. The important point is that some of the models (i.e. ANN) are able to give reasonable results that suggest an understanding of the underneath relation of this problem, even when no optimization of hyperparameters has been done and really naive example models have been used. Even if results from ANN are not as high as expected when analyzing class by class, they are still good enough for assuming that with improvements both in the model and in the database, good prediction can be achieved.

An important aspect to note in Table 6's results is that the distribution of samples along classes is not balanced, being much more examples in classes 4 and 5 than in the others, as can be seen in Table 7. This can explain the difference in accuracy depending on the class.

Table 7: Distribution of samples along classes.

Class	**Training**	**Test**
1	502	121
2	95	20
3	878	224
4	10448	2643
5	19265	4792

Generating new samples or replacing some from the more populated classes with samples of the others should improve prediction along with every class, given a more balanced result.

Another limitation that should be noted on this system in its current form is that it assumes equally reliable sources. The next step is to include it as a new input feature of the system. However, regarding the promising results that some techniques (i.e. ANN) suggest, accounting for the reliability of the sources may be feasible by these techniques.

Nevertheless, providing that the relation between geometries and classes can be modeled by an ML technique if more effort is put on tuned the model and improved the databases, it means that when a conjunction event between two space objects is detected along with the uncertainties in position, the AI system can provide to the operators the best option for implementing a decision, accounting for the evidence associated with the epistemic uncertainty of the encounter. Not only that but also doing in a much shorter period of time. Since the longer step in the process is computing Belief and Plausibility, due to the search of maximums and minimums in each Focal Element, using this system enables to speed up the whole process.

5 Conclusions

In this paper, the concept of Belief and Plausibility from Evidence Theory has been applied in the field of STM, specifically on conjunction risk assessment. Current metrics for evaluating the risk of an encounter are affected by dilution of probability, which is rooted in the way epistemic uncertainty is treated in classical approaches. Evidence Theory applied for conjunction risk assessment has been proved to be a useful approach to overcome some of the problems associated with dilution of probability, especially when combining information from different sources.

Since, in some cases, these new concepts can lead to a different conclusion than previous methods regarding the risk of a space encounter, a new classification of events has been proposed. This classification differs from the previous one that it is not based on the value of the probability of collision, but on the confidence (Belief and Plausibility) will have of those values, regarding the evidence provided by the sources.

The classification criteria proposed here uses five parameters from a single event to propose a class for it: time to the encounter and the values of Plausibility and Belief at two P_C thresholds selected by the operator. The class output by the system is a proposal for the operator to support him on the decision -making processes like performing a CAM, prepare a one for an eventual execution or simply collect more reliable data if there is enough time. However, other parameters coming from Evidence Theory, like the distance between Plausibility and Belief, can be taken into account for proposing more sophisticated classifications regarding the needs of operators as well as the level of risk they would be able to admit.

Finally, two AI-based systems have been proposed for atomizing the decision-making process by classifying the events accordingly to the proposed classification. A preliminary analysis of the capabilities of different ML techniques for classifying different encounter geometries has been tested. It was shown that, even for very simple models, they were able at least to find the underneath relation that drives this problem, if not to perform very good predictions. One of the systems uses as inputs exactly the same variables used to define the classes and provide very accurate results even with no optimized model's hyperparameters. The other system, while providing less accurate results for the models tested, shows the possibility of using these techniques for avoiding the time-consuming step of computing Belief and Plausibility of the given event, and predict its class only using the geometry proposed by sensors. It means that a reliable, computationally cheap and fast automatize system can be designed for support operators on the decision-making process in collision risk management.

However, some aspects can and should be improved, both in the application of Evidence Theory on collision risk assessment as well as in the implementation on an AI-based system for classifying risky events:

- Risk evaluation is still assessed assuming Normal Distributions and using Equation 1. It means, that some problems related to the probability of dilution still apply. Further improvement on the way Evidence Theory is implemented and the parameters it takes into account should be made. In further steps, a new formulation for avoiding the use of Equation 1 should be also made.
- The proposed classification of events is just an initial proposal for accounting for epistemic uncertainty. However, there is room for improvement. Some of them are taking into account more variables for refining the classification (i.e. the distance between Plausibility and Belief curves) or possibilities of tuning the classification regarding the level of risk the operator want to assume: including different thresholds for Plausibility and Belief, accounting for future consequences, risk of preforming a maneuver...
- Although it is likely that ML techniques can be applied for this situation, a more detail analysis should be performed to find the best technique. Also, a search for optimum hyperparameters should be implemented.
- Accounting for the reliability of the sources should be an improvement to be implemented shortly for the second AI system presented in the paper.
- Regarding the database, for future works, the ideal situations would be using real data for creating the database or using events predicted by orbit propagation (from real or virtual satellites). However, other points can be previously considered for improving these datasets: using wider ranges of geometries, with bigger intervals, bigger values of mean values and standard deviations... in order to be closer to real data, or using the conjunction events predicted by propagators or surrogate propagation models (of real or created satellites).
- Finally, works are suggested to follow the path of combined the AI-based system with other decision support systems. In this sense, using results for surrogate propagation models based on ANN techniques to feed this system is an interesting proposal. Other possibilities can be found on the combination of this system with a collision avoidance maneuver proposal system and system for predicting future consequences (based on future collision, propagation of corrected orbits...), in order to create an AI-based Decision Support System for the whole process of STM.

References

[1] "ESA's Annual Space Environment Report". In: *ESA Space Debris Office, ESOC-ESA* GEN-DB-LOG-00271-OPS-SD.3.2 (July 2019).

[2] G. Peterson, M. Sorge, and W. Ailor. "Space Traffics Managemetn in the age of New Space". In: *The Aerospace Corporation. Center for Space Policy and Strategy* (Apr. 2018).

[3] D. Izzo, M. Märtens, and B. Pan. "A survey on artificial intelligence trends in spacecraft guidance dynamics and control". In: *Astrodynamics* 3.4 (Dec. 2018), pp. 287–299.

[4] H. Peng and X. Bai. "Exploring Capability of Support Vector Machine for Improving Satellite Orbit Prediction Accuracy". In: *Journal of Aerospace Information Systems* 15.6 (2018), pp. 366–381.

[5] Hao Peng and Xiaoli Bai. "Artificial Neural Network–Based Machine Learning Approach to Improve Orbit Prediction Accuracy". In: *Journal of Spacecraft and Rockets* 55.5 (2018), pp. 1248–1260.

[6] M. Vasile et al. “Artificial Intelligence in Support to Space Traffic Management”. In: *68th International Astronautical Congress, Adelaide, Australia* (Sept. 2017).

[7] L. Sanchez, M. Vasile, and E. Minisci. “AI to support decision making in collision risk assessment”. In: *70th International Astronautical Congress, Washington, USA* (Sept. 2019).

[8] R. Patera. “General Method for Calculating Satellite Collision Probability”. In: *Journal of Guidance Control and Dynamics - J GUID CONTROL DYNAM* 24 (July 2001), pp. 716–722.

[9] S. Alfano. “A numerical implementation of spherical object collision probability”. In: *Journal of the Astronautical Sciences* 53 (Jan. 2005), pp. 103–109.

[10] S. Alfano. “Review of conjunction probability methods for short-term encounters”. In: *Advances in the Astronautical Sciences* 127 (Jan. 2007), pp. 719–746.

[11] R. Serra et al. “Fast and Accurate Computation of Orbital Collision Probability for Short-Term Encounters”. In: *Journal of Guidance, Control, and Dynamics* 39 (Jan. 2016), pp. 1–13.

[12] S. Alfano and D. Oltrogge. “Probability of Collision: Valuation, variability, visualization, and validity”. In: *Acta Astronautica* 148 (Apr. 2018).

[13] M. Balch, R. Martin, and S. Ferson. “Satellite conjunction analysis and the false confidence theorem”. In: *Proceedings of the Royal Society A: Mathematical, Physical and Engineering Sciences* 475 (July 2019).

[14] G. Shafer. *A mathematical theory of evidence*. Princeton University Press, 1976.

[15] L. Newman et al. “Evolution and Implementation of the NASA Robotic Conjunction Assessment Risk Analysis Concept of Operations”. In: *Advanced Maui Optical and Space Surveillance Technologies Conference* (Sept. 2014).

[16] K. Merz et al. “Proc. 7th European Conference on Space Debris, Darmstadt, Germany”. In: *Journal of Statistical Computation and Simulation* (Apr. 2017).

[17] M.H. Hassoun. *Fundamentals of Artificial Neural Networks*. Ed. by USA © MIT Press Cambridge MA. First Edition. 1995. isbn: 026208239X.

[18] *MATLAB Deep Learning Toolbox*. `https://uk.mathworks.com/help/deeplearning/index.html`.

[19] L. Breiman. “Random Forest”. In: *Machine Learning* 45 (1 Oct. 2001), pp. 5–32. doi: `10.1023/A:1010933404324`.

[20] *Python Scikit learn library. KNN Classifier.* `https://scikit-learn.org/stable/modules/generated/sklearn.neighbors.KNeighborsClassifier.html#sklearn.neighbors.KNeighborsClassifier`.

[21] Charles Elkan. “Nearest Neighbor Classification”. In: (Feb. 2011). doi: `10.1007/978-0-387-39940-9_2920`.

[22] *Python Scikit learn library. RFF Ensemble Classifier.* `https://scikit-learn.org/stable/modules/generated/sklearn.ensemble.RandomForestClassifier.html`.