A Depth Control Pruning Mechanism for Multiple Hypothesis Tracking

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Abstract - Computational requirements represent the main drawback of the Multiple Hypothesis Tracking (MHT) data association algorithm. To reduce these requirements, the number of hypotheses must be limited through the use of pruning methods. This paper presents a depth control pruning mechanism making hard decisions on the origin of input data elements contained in the hypothesis tree. Inherently, the MHT uses later input data to aid in evaluating prior correlation decisions. Ultimately though, a final decision has to be made. The depth control mechanism is used to transfer the assignment of an input data element from the "hypothetical" section of the hypothesis tree to the "definitive decision" section. The waiting period is determined by the number of target observation attempts made that can be used to resolve a particular assignment. The occurrence, the duration, the quality and the result of a target observation attempt are concepts discussed in the paper. Some depth control pruning simulation results are also presented.

Keywords: multiple hypothesis tracking, MHT, data association, pruning, hypothesis tree

1.0 Introduction

From the point of view of tracking multiple targets in a cluttered environment, the data association process can make either hard decisions or soft decisions about which of a number of hypotheses best describes the origin of input data elements received from a sensor. A hard decision is a definitive assignment to one and only one origin, while a soft decision allows the data to be assigned to multiple origins, with each candidate assignment having a measure of uncertainty. The soft decision approach typically results in multiple association hypotheses being maintained until additional input data elements have been collected and there is enough information data available to reduce the uncertainty and to substantiate or refute the prior hypothetical assignments. In principle, this approach should lead to the most accurate association results. However, the computational requirements necessitated to retain multiple interpretations of the situation represent the main drawback of the standard (hypothesis oriented) Multiple Hypothesis Tracking (MHT) data association algorithm (Refs. 1-8).

To reduce these computational requirements, the number of data association hypotheses must be limited (sometime sacrificing optimal Bayesian inference) through the use of hypothesis pruning and combining methods. In terms of pruning, both the width and the depth of the hypothesis tree (i.e., the number of hypotheses maintained and the number of levels in the tree respectively) can be controlled. This paper presents a depth control pruning mechanism that forces hard (or definitive) decisions on the origin of input data elements contained in the hypothesis tree.

The paper is organized as follows. Section 2.0 discusses the hypothesis tree of the MHT and the dynamic data structure used to implement it. Section 3.0 gives a brief introduction to width pruning while section 4.0 describes the depth control pruning mechanism in length. Section 5.0 discusses the concept of target observation attempts and, finally, section 6.0 presents some depth control pruning simulation results.

2.0 The hypothesis tree

Central to the MHT approach is the formation of a hypothesis tree. The discussion in this paper focuses on the standard MHT algorithm implementations (i.e., those that support explicit hypothesis propagation over time as in Refs. 1-2) as opposed to the implementations based on structured branching (SB/MHT, Refs. 3-8).

When there is no limitation, all possibilities concerning the origin of received input data elements are enumerated as alternative hypotheses organized in a tree (Fig. 1). These hypotheses contain groupings of some input data elements into tracks, and the identification of other such elements to be false targets (Refs. 1-2). As a new set of input data elements is received, a new set of data association hypotheses is formed by extending the existing prior hypotheses of the tree with the feasible correlation hypotheses that account for all possible origins of the new input data elements.

The growth of hypotheses must however be limited if the MHT implementation is to be feasible. Hence, before a new hypothesis is created, the candidate track must typically satisfy a set of conditions (e.g., require that an input data element...
satisfies a gating relationship before an assignment to a track is made, etc.).

There are three kinds of tree nodes: root, sub-interpretation and hypothesis. Since a data association hypothesis is indeed a unique interpretation of the origin of each measurement, the nodes of the tree are considered to be sub-interpretations, each one being applicable to a specific measurement. Hence, a given hypothesis is represented in the data structure as one particular sequence of sub-interpretations (considered together as one possible global interpretation of the origin of all the received data) that are linked from the root node up to a special sub-interpretation node (called hypothesis) at the other end of the tree.

Each input data element record is linked to one or more affectations representing the possibilities for this measurement. Each affectation is linked to only one input data element. However, an affectation can be linked to one or more tree nodes and one or more child affectations. A child affectation is an affectation of a measurement to the update of a previously established track. This concept of parent-child affectations is used to represent the different track families of the hypothesis tree.

A level exists in the hypothesis tree for each input data element. Levels may also be created to accommodate targets whose existence is known a priori. Fake "input data elements" provided by the initialization procedure are then affected to these known targets. The level of each sub-interpretation in the tree is indicated between brackets (level 0 being the root level), and each sub-interpretation has also a number that follows the hypothesis numbering scheme up to that level (Fig. 2).

Note that the hypothesis numbering follows the scheme described in Refs. 1-2. One important aspect of the standard numbering scheme is that an internal system track, once created by the assignment of an input data element to it, can only progress towards its deletion by the track management system (as a result of a decrease in its quality, or because of the pruning of some relevant branches of the hypothesis tree). This is so because the track will keep its number (the one that has been used at its creation) only if it is not updated; the internal track number will change (thereby creating a "new" internal system track) as soon as the track is considered updated in any given hypothesis.

3.0 Width pruning

If implemented without severe limitation mechanisms, the MHT algorithm requires an ever-expanding memory as more data are received and processed. Hence, the growth of the hypothesis tree must clearly be limited for a feasible implementation on a computer (Refs. 1-2). The goal is a data
association algorithm that requires a minimum amount of computer memory and execution time while retaining nearly all the accuracy of the optimal procedure.

As discussed above, the hypotheses may be considered as branches of a tree. The hypothesis reduction techniques may thus be viewed as methods of either pruning or binding together these branches. In terms of pruning, both the width and the depth of the hypothesis tree (i.e., the number of hypotheses maintained and the number of levels in the tree respectively) can be controlled. Reference 2 describes four width-pruning approaches in details (i.e., probability, probability sum and ratio of probabilities thresholding, and fixed number).

4.0 Depth control pruning

Inherently, the MHT uses later input data to aid in evaluating difficult prior correlation decisions concerning prior input data. Hence, for each new input data element, the MHT generates soft association decisions and then waits (i.e., defers the final decision as to the right assignment) until further observations resolve the matter as best as possible. Based on this fundamental principle, one could be tempted to let the hypothesis tree grow forever (i.e., retain all hypotheses) with the conviction that the bigger the tree is (i.e., the longer the waiting period is), the better the information available is to make an educated decision on the origin of a particular input data element. Ultimately though, a final, hard decision has to be made for the system to be practical. This is the main consideration behind the depth control pruning mechanism discussed in this paper. That is, it is useless to accumulate evidences about the occurrence of an event if no decision is made about it at the end of the day.

This hard/soft decision concept leads directly to the notion of hard and soft zones in the hypothesis tree. A particular tree level is thus said to be in the "soft decision zone" of the hypothesis tree when there are multiple alternatives for the interpretation of the origin of the corresponding input data element. When there is only one option left for the explanation of the origin of an element, then the corresponding level is said to be in the "hard decision zone" of the hypothesis tree. Figure 3 is a graphical illustration of this zone concept. Note, however, that the situation depicted in Fig. 3 (i.e., hard zone on the left and soft zone on the right) is purely academic. Plausibly, since an effort is made to keep the arrival sequence of the input data elements intact in the tree, the definitive assignments and the hypothetical affectations would be mixed and spread over the entire length of the data structure in a realistic example. This has no consequence on the results.

![Hypothesis Tree Diagram](image)

**Figure 3. The hard and soft zones concept**

In view of the considerations above, the depth control pruning mechanism is a set of rules used to transfer (logically only) the interpretation of the origin of an input data element from the hypothetical (or soft) decision zone of the hypothesis tree to the definitive (or hard) decision zone. One should note that, although the assignments attached to the hard decision zone are final, there is a reason to keep the input data elements, affectations and tree nodes in this zone for some time after they have been transferred by the depth control procedure. Any affectation must be kept in the hypothesis tree (whatever the zone it is in) for as long as the track it represents is still "reproductive". By definition, a reproductive track is one that can still be considered for association with new input data from the sources. Therefore, a reproductive track can eventually generate new tracks, which are considered as its "children", and the affectation matching such a track must thus be kept to ensure the consistency of the growth of the hypothesis tree.

A track that is marked for deletion by the track management logic is not considered anymore for association with new input data from the sources; such a track is, by definition, a "sterile" track. Note that a track may become sterile as its quality falls below some minimum or as a result of a pruning operation on the hypothesis tree (i.e., when the only hypotheses left in the tree are the ones where the track has already been updated with an input data element). The rule for a sterile track is that it must be kept in the hypothesis tree if it is still in the soft decision zone of the tree (since a final decision about the best interpretation of the origin of the corresponding input data element has not been made yet). Hence, an affectation (and the related input data element and tree node) can be ultimately removed from the tree if 1) it is in the hard
decision zone and 2) the corresponding track becomes sterile. In a sense, this last pruning operation is the ultimate "depth control" step limiting the size of the overall tree (i.e., not only the size of the soft zone).

The decision to transfer a tree level from the soft zone to the hard zone can be based on the monitoring of discrete or continuous parameters. For the discrete version, the waiting period for triggering the depth control pruning mechanism is determined by the number of target observation attempts made that can be used to resolve a particular assignment. That is, the waiting period is set by the observation attempt depth, not by the physical depth of the hypothesis tree.

The physical depth is useless to settle a correlation conflict between different tracks for a given input data element if none of the other data elements has something to do with the one being resolved. With a scanning sensor for example, if 10 observations were received at the end of a given scan, then the hypothesis tree will be augmented with 10 new levels. In such a case, although the tree may be considered as "deep", no truly educated decision can be made about any assignment of the 10 new observations. The 10th observation of the data set doesn't tell anything about how the 1st should be interpreted. And this is true of any of the 10 observations. However, if these observations were received in 10 distinct scans, then the reception of say the 6th observation could help with the resolution of the assignment of say the 1st. Similarly, the reception of say the 10th observation could help with the decision on the explanation of the origin of say the 6th. This is so because later scans constitute additional target observation attempts that have been made, each one producing some result (hit or miss), and that can thus be used to substantiate or refute prior data associations that are still considered hypothetical.

With respect to the actual implementation, a hard decision is made at one level of the tree (i.e., for the explanation of the origin of a specific input data element) when all affectations at this level have received a prescribed number of target observation attempts (a configurable parameter). When this is the case, the affectation having the highest likelihood (as determined by the sum of the likelihood of all hypotheses ensuing from this affectation) is retained as the best, final assignment for the input data element. All hypotheses linked to the other affectations of the element are then pruned from the tree. This procedure greatly reduces the number of hypotheses to be maintained.

The mechanism described above requires that a count be kept for an affectation (i.e., for the track created by the affectation) of the number of subsequent observation attempts that have been made and that are relevant to this affectation. The results of these attempts (hits or misses) are reflected in the hypothesis tree by the actual hypotheses following the affectation, and their likelihood.

Obviously, the higher the number of sources reporting on a target is (i.e., the higher the observation attempt rate is), the faster hard decisions can be made on the affectations. This is an immediate benefit of sensor data fusion.

### 5.0 Target observation attempts

The notion of "target observation attempts" is at the heart of any track management system and it is also the key concept behind the depth control pruning mechanism. A target observation attempt is defined as an opportunity to acquire information for the maintenance of a track on a hypothesized target entity. The occurrence, the duration, the quality and the result of a target observation attempt are important concepts that are discussed next.

#### 5.1 Observation attempt occurrence

Some logic must determine when target observation attempts will occur (or should have occurred). This is a very important issue that has multiple facets: the use of scanning type sensors (some potentially reporting data based on a spatial decomposition into sectors), the use of multiple sensors, the use of agile beam sensors (e.g., electronically scanned antennas), etc. Taking into account all of the aspects above, a mechanism is required to determine the observation opportunities for each individual track with respect to each individual source. A very accurate model could quickly become very complex. Note, however, that the complexity of this model must not be greater than the one of the MHT implementation that one is trying to simplify.

#### 5.2 Observation attempt duration

Very often, there is a significant duration associated with any target observation attempt when using a scanning type of sensor. This time interval results from the uncertainty on the estimated kinematics properties of the targets. The scanning sensor must sweep the totality of the area of uncertainty for a target before an observation attempt occurrence is declared for this target.

#### 5.3 Observation attempt quality

It is very important to assess the quality of an observation attempt in order to derive a meaningful interpretation of the result of this attempt. For example, one should not be surprised when a particular target is not detected if the observation conditions for
this target are really bad. Similarly, if the observation conditions for a particular target are really bad, then one should be surprised if this target is actually detected; the received input data element is probably a false alarm in this case. Finally, if the observation conditions for a particular target are really good, then one should question the existence of a hypothetical target if this target is not detected.

Factors typically taken into account in the evaluation of the quality of observation attempts include:

Sensor-Target Geometrical Factors: A target may be momentarily obscured by terrain obstacles (e.g., the earth curvature, a mountain, etc.) or it may have left the coverage of the sensor (e.g., the elevation coverage). If a sector based report grouping mechanism is used, it may happen that a target is not in the current sector of interest (e.g., the target may have already been observed in a previous sector, or it may eventually be observed in a subsequent sector). These factors have an impact on the probability of detection value \( P_d \) and the density of new objects per attempt per unit of volume (i.e., \( \beta_{VT} \) and \( \beta_{FT} \)). Note that the uncertainty on the estimated kinematics properties of a target must be taken into account with the geometrical factors.

Sensor System and Environmental Factors: Sensor configuration parameters (transmitter power, scan mode, blind zones, etc.) and environmental conditions (e.g., sea state, rain, etc.) affect sensor performance (i.e., \( P_d \)).

Track Duration/Length Factors: A target may have left the coverage of the sensor (e.g., a target with a radial outbound flight profile) or may have disappeared (e.g., the target has been destroyed).

Hence, for each observation attempt that is made, some process must determine if the attempt is a good one or not. Note that the concepts of occurrence and quality of observation attempts are tightly coupled. Should the occurrence of an attempt with a null quality still be considered an occurrence? Once again, the complexity of the quality model must not be greater than the one of the MHT implementation that one is trying to improve.

5.4 Observation attempt result

Basically, there are two possibilities for the result of an attempt:

No Detection: The observation attempt has been unsuccessful. This is called a "missed observation attempt", or, more simply, a miss.

Sensor Data Available: The sensor has provided some data as a result of the attempt. Generally however, there is ambiguity as to the origin of the sensor data provided. An input data element may originate from a target that was already known and monitored (the element could thus be used to update the corresponding track), or it may originate from a new object (i.e., a new target previously undetected or a false alarm).

In any case, one has to assess the result taking into account the quality of the attempt that has been made.

6.0 Depth control simulation results

Two simulation examples have been produced, using the CASE_ATTI (Concept Analysis and Simulation Environment for Automatic Target Tracking and Identification) test bed developed at Defence Research Establishment Valcartier (DREV), to illustrate the behavior of the depth control pruning mechanism. This test bed provides the algorithm-level test and replacement capability required to study and compare the technical feasibility, applicability and performance of advanced, state-of-the-art sensor fusion techniques (Ref. 9).

6.1 First example: depth control impact

The first example has been designed to illustrate the impact of the depth control pruning mechanism on the computer resources requirements for the MHT. A very simple target-tracking scenario has been defined for this example. The scenario features two targets that appear one after another to illustrate the growth and decay of the hypothesis tree. The first target appears after 50 s of simulation. Its initial position is \( x = -31.25 \text{ km}, y = 25 \text{ km} \) from the origin, at an altitude of 1 km. The target then travels along the x-axis (positive direction) at a constant speed of 250 m/s for 100 s. It then disappears from the simulation. After another 50 s without a real target, the second target appears at \( t = 200 \text{ s}, x = 6.25 \text{ km}, y = 25 \text{ km} \) at an altitude of 1 km. It also travels along the x-axis (positive direction) at a constant speed of 250 m/s for 100 s. The second target then disappears from the simulation. After another 50 s without a real target, the scenario ends at \( t = 350 \text{ s} \).

During the whole scenario (i.e., from 0 to 350 s), a simulated scanning sensor, located at the origin, samples the environment at a rate of 60 RPM. This is an "academic" type of sensor simulation where the probability of detection for the targets has been set to a constant value of 1. Hence, when a target is present, it is detected and a measurement of the target position is produced once every second. The simulated sensor also generates false measurements, uniformly distributed in the overall coverage of the sensor, at an average rate of one per scan.

The resulting simulated data, shown in Fig. 4, was used twice to feed a target tracking system running the MHT. The track confirmation logic was set to three
hits out of five attempts, while the track deletion criteria was set to 10 s without a track update. In the first run, the Depth Control Metric Threshold (DCMT) of the depth control pruning mechanism was set to 5 observation attempts. In the second run, the same threshold was set to 1. In both cases, the tracking system successfully formed a firm, accurate track on each of the two targets, without generating any false track. However, the resources required by the MHT were not the same for the two runs.

Three parameters, i.e., the depth of the hypothesis tree, the number of hypotheses maintained and the number of internal system tracks stored in the track database, were monitored for each run. Figure 5 shows the evolution of the depth of the hypothesis tree during the first run. Both the depth of the hard decision zone alone and the total depth of the tree (i.e., hard and soft zones) are shown. One can clearly identify on the graph the two time intervals where the real targets were present in the scenario (i.e., [50, 150] and [200, 300]). The number of tree levels augmented significantly during these intervals when the tracking system was not fed with false measurements alone. The maximum number of tree levels attained during the run was 16 (the minimum was obviously 1), while the average number of levels was 8.44.

Note that the number of levels in the hard decision zone was exactly 1 when a real target was present (indeed, it took 5 s after the appearance of the target to attain 1, and it took 10 s after its disappearance to go back to 0), while it is 0 when the tracking system processes only false measurements alone. The maximum number of tree levels attained during the run was 16 (the minimum was obviously 1), while the average number of levels was 8.44.

Figure 4. Simulated data for the first example

Figure 5. Tree depth (DCMT = 5)

Figure 6. Hypotheses maintained (DCMT = 5)

Figure 7. Tracks stored (DCMT = 5)

Figure 6 shows the evolution of the number of hypotheses maintained in the tree during the first run. Again, one can clearly identify on the graph the two time intervals where the real targets were present. The maximum number of hypotheses allowed in the tree (a configurable saturation parameter of the MHT) was set to 10,000. This maximum was reached a number of times during the intervals where the real targets were present. Note that the maximum allowed could have
been set to a much lower value without degrading the tracking performance. However, we wanted to illustrate how an uncontrolled MHT can be resource demanding. Hence, the maximum number of hypotheses attained during the run was 10,000 (the minimum was obviously 2), while the average number was around 2400. Note that during the portions of the simulation without a target, the number of hypotheses maintained was always a power of 2 (e.g., 16, 64, 1024, etc.), which was not the case in the other segments.

Finally, Fig. 7 shows the progress of the number of internal system tracks stored during the first run. The maximum number of tracks was 100 (the minimum was obviously 1, a new potential track), while the average number was around 32. During the intervals where the real targets were present, the average number of tracks was around 40.

Figures 8 to 10 show the evolution of the same three parameters for the second run, with the DCMT set to 1 observation attempt. One can without a doubt see that the depth control pruning procedure greatly reduces the computer resources requirements for the MHT; the size of the hypothesis tree maintained has been significantly reduced. Figure 8 shows the progress of the depth of the hypothesis tree during the second run. It is not as easy to identify on the graph the two time intervals where the real targets were present. The maximum number of tree levels attained was 8 (again the minimum was obviously 1), while the average number of levels was 3.33. Note that the number of levels in the hard decision zone of the tree fluctuated more than in the first run, reaching a peak value of 3 while maintaining an average value close to 1.

The number of hypotheses maintained (Fig. 9) has also been radically reduced, and no saturation condition was observed. The maximum number of hypotheses maintained during the second run was 96 (again the minimum was obviously 1), while the average number was around 10. Note that during the portions of the simulation without a target, the number of hypotheses maintained was not always a power of 2, reflecting the higher difficulty of the MHT to maintain the data association accuracy. Finally, Fig. 10 shows the progress of the number of internal system tracks stored during the second run. The maximum number of tracks was 11 (the minimum was obviously 1, a new potential track), while the average number was around 6.

As a final remark for the first example, note that the edge of the transitions from one interval to the other (target, no target) were not as sharp in the second run with the DCMT set to 1 as they were in the first run with the DCMT set to 5. In a sense, this reflects the association discrimination power of the MHT when it is allowed to keep more information to make the final decision.

![Figure 8. Tree depth (DCMT = 1)](image)

![Figure 9. Hypotheses maintained (DCMT = 1)](image)

![Figure 10. Tracks stored (DCMT = 1)](image)

### 6.2 Second example: optimal DCMT setting

The second example has been designed to illustrate the trade-off between the data association accuracy and the computer resources requirements for the MHT. Again, a very simple target-tracking scenario was defined for this example. The scenario features two closely spaced targets flying in parallel (with a separation of 600 m), along the x-axis (positive
direction), at about 25 km from the sensor. The two targets were observed during 100 s by a simulated scanning sensor located at the origin and having a scan rate of 60 RPM. The probability of detection was set to 0.8. The standard deviations of the measurement errors for the simulated sensor were 500 m in range and 0.02 radian in bearing. No false alarms were generated.

The resulting simulated data shown in Fig. 11 were used three times to feed a target tracking system running a nearest-neighbor (NN) data association algorithm for the first run, and the MHT for the last two runs (with the DCMT set to 1 and 5 respectively). The track confirmation logic was set to three hits out of five attempts, while the track deletion criteria was set to 10 s without a track update.

Figures 12 to 14 show the tracking results for the three runs. One can see that the tracking system using the NN algorithm (JVC technique) had a hard time tracking the two targets (Fig. 12). Three firm tracks were established on the two targets. In the first half of the run, the tracks were very unstable. During the last portion of the run, two tracks followed the same target, while the third one diverged from the other target.

Figure 13 shows the tracking results for the second run, with the DCMT set to 1 for the MHT. This time, two tracks were established. However, one of the tracks was only confirmed after about 50 s of simulation, while the other exhibited a track seduction behavior (i.e., the track initially followed one target, then the other target, then the first target again, etc.). The maximum number of tree levels attained during this run was 4 while the average number of levels was around 3. The maximum number of hypotheses attained was 20 while the average number was around 9. The maximum number of internal tracks was 14 while the average number was around 10.

Finally, Fig. 14 shows the tracking results for the third run, with the DCMT set to 5 for the MHT. In this case, the tracking system successfully tracked the two targets for the whole duration of the run, without generating any false track. The maximum number of tree levels attained during the third run was 9 while the average number of levels was 6.6. The maximum number of hypotheses attained was 100 (i.e., the saturation condition set for this run) while the average number was around 58. The maximum number of tracks was 166 while the average number was around 100.

This example clearly demonstrated that there is a trade-off between the data association accuracy (and consequently the tracking stability and accuracy) and the computer resources requirements of the MHT. An optimal setting for the DCMT parameter remains to be found that would result in a balance between tracking performance and resources utilization.

7.0 Conclusion

To reduce the computational requirements of the MHT data association algorithm, the number of hypotheses must be limited through the use of pruning methods. This paper presented a depth control pruning mechanism making hard decisions on the origin of input data elements contained in the hypothesis tree. It is used to transfer the assignment of an input data element from the soft decision zone of the hypothesis tree to the hard decision zone. The waiting period is determined by the number of target observation attempts made that can be used to resolve a particular assignment. Obviously, the higher the number of sources reporting on a target is (i.e., the higher the observation attempt rate is), the faster hard decisions can be made on the affectations. This is an immediate benefit of sensor data fusion. The occurrence, the
duration, the quality and the result of a target observation attempt are concepts that were discussed in the paper. A model is required to determine the observation opportunities for each individual track with respect to each individual source, and to evaluate the quality of the attempts. However, a very accurate model could quickly become very complex. Clearly, the complexity of this model must not be greater than the one of the MHT implementation that one is trying to improve.

Some depth control pruning simulation results were presented. Two simulation examples have been produced using the CASE_ATTI test bed developed at DREV. The first example has been designed to illustrate the impact of the depth control pruning mechanism on the computer resources requirements for the MHT. Results showed without a doubt that it is possible to greatly reduce the computer resources requirements for the MHT with the depth control pruning procedure while, in some conditions, keeping the accuracy of the tracking process. In particular, it is manifest that if the depth of the tree is well controlled, then the width pruning mechanisms may never have to be used (i.e., the saturation conditions may potentially never be met).

However, the second simulation example presented showed that a trade-off between the data association accuracy (and consequently the tracking stability and accuracy) and the computer resources requirements of the MHT has to be made when the situation portrays high potential for correlation ambiguities.

Further work is required to better characterize the depth control pruning mechanism in order to find the optimal depth of observation attempts that would maximize the data association accuracy and minimize the resources requirements. The option to adaptively select the optimal depth for a given environment must also be investigated.

8.0 References