Dynamic Morphological Exploration

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Abstract: Morphological Analysis of even moderately complex systems, can lead to large (often unmanageable) state spaces. In many contexts, the expense of testing or exploring a single state can make exploration of the entire state space prohibitive. To temper this, techniques and software packages have been designed to assist the analyst in 'spanning' the total morphological space using a minimal number of assessments.

However, the authors have noted situations where the determination, *a priori,* of a (static) set of states to test has led to highly sub-optimal exploration of the problem. This has been due to the analysts not being able to predict, and account for, the results of complex interactions of all the variables. Initial assumptions on the magnitude of impact from minor factors has canalised the analysis plans down dead-ends.

To address this problem, and extension of General Morphological Analysis is proposed: Dynamic Morphological Exploration.

The driving principle behind this method is to create an exhaustive tree mapping of optimal search paths, based on all possible outcomes of previous state space tests. The analyst is then able to refer to the Dynamic Morphological Exploration Tree during an experiment or analytical campaign to objectively decide the next set of parameters to tested. With sufficient fore-thought, the Tree will guide the analyst away from repetition and dead-ends.

This paper first describes the principles behind generating Dynamic Morphological Exploration Trees. It then uses an example to generate a sample tree and shows how this approach is superior to the more traditional approach of exploring Morphological Spaces.

Keywords: *Morphological Analysis, Scenario Analysis, State Space Exploration*

1. INTRODUCTION

Wicked Problems have long been discussed in relation to their 10 characteristics, as described by Rittel and Webber (1973). The sixth characteristic, "*Wicked Problems do not have an enumerable set of potential solutions*", implies the set of scenarios or options to consider is generally unmanageable. This lends itself to applying a General Morphological Analysis approach (Zwicky (1948), Ritchey (2011b)).

The complication arises, however, in the fact that it is not always feasible or possible to test all (or even many) of the potential solutions identified within a morphological space (Eriksson and Ritchey (2005)). To overcome this there is a need to target those parts of the morphological space that will maximize the information gained about the problem. One useful approach when considering issues such as changes in capability, is that of determining the boundary of the Feasible Friendly Scenario Space (FFSS) (Grisogono *et al.*, 2013). The FFSS represents that area of the morphological space in which a given friendly capability can operate within an acceptable level of risk. Thus defining this boundary determines what parts of the morphological space can be achieved by a given capability. For brevity the boundary of the FFSS will be referred to as the FFSS in this paper.

This means that determining the states of the morphological space for analysis *a priori* can often lead to poor use of resources. In particular, the authors have experience with running activities which use military wargames to explore the impact of different capabilities and plans within various environments, and against different enemy forces. Often, time and personnel constraints mean only in the order of 10 such wargames can be run. Hence, the analyst needs to have a plan of attack in exploring the morphological space that is both dynamic and intelligent.

2. GENERAL MORPHOLOGICAL ANALYSIS

General Morphological Analysis (GMA) is a common technique used to structure and investigate the behaviours and solutions to complex or wicked problems (Ritchey (2004), (2011a), (2011b), Zwicky (1948), Wissema (1976)). The basic concept is to draw out the key dimensions or factors of the system and, for each, enumerate the full set of potential values those factors may take. The exhaustive list of permutations of the values then forms the complete morphological space (sometimes referred to as a Zwicky box).

A series of cross-consistency assessments are made on the permutations to single out solution states that are either logical contradictions, empirical constraints or normative constraints (Ritchey (2009)). This reduces the morphological space, but it is still possible to be left with hundreds, if not thousands, of potential solution states (Eriksson and Ritchey (2005) and Ritchey (2009)).

In some situations all of these can be effectively assessed or tested. Even if a tool such as agent based distillations (Horne, 2001) is an applicable method, combinatorial blow-out can cause the state space to be intractable. For Wicked Problems, where more expensive analytical techniques are required, the analyst may only have the resources to examine a few states.

2.1. Prioritising High Value States

For cases where exploration of the morphology space is very expensive (in terms of time or resources), a very small subset of the state space can be tested – in the order of 10 – 20 or fewer states (Bowden *et al.* 2009), Proposka (2001), Shine and Coutts (2006)). It falls to the analyst and the stakeholder, therefore, to prioritise which of the possible solutions to examine. This selection process could follow any number of guides, such as attempting to maximise the span of the morphological space covered, concentrating on the most likely successful options, the solutions that fit easily within the resource constraints, or any combination of these.

Although these approaches may be applicable for some wicked problems, often within these types of problems the analysts cannot be sure which are the most beneficial states to address the problem at hand until they have been studied. This is particularly the case when considering new options to wicked problems such as novel or predicted capabilities or work practices.

This problem is further complicated as the analysis process required takes significant time to put in place. Thus, the prioritisation of high value states to include within the study need to be determined as the study progresses, but ideal paths need to be pre-determined.

2.2. Dynamic Morphological Trees

To help address this problem, an extension to GMA is proposed; Dynamic Morphological Exploration (DME). A 'DME Tree' is defined after the morphological space and cross-consistency analyses have been done. This Tree is then used to guide the subsequent analysis to maximise the benefits of the limited available state space tests.

To begin, one or more starting high value states are chosen. These can be defined in a number of ways. Some possible methods include defining these based on the most likely elements of the reduced morphological space; looking for elements of the morphological space that have cause problems in the past; and advice from SMEs on elements of the morphological space that represent primary areas of concern. A set of possible outcomes is anticipated from testing these states. For example, the results could be a simple pass or fail, or even a spectrum of success ratings.

Each one of these expected outcomes is then assigned the most valuable next state to test *based on the result*. That is, the previous assessments of solutions will dynamically alter which subsets of the whole morphological space become more important to the study.

The branching continues until the full quota of tests is filled, or until a subspace of the morphological space is sufficiently addressed. At this point, if tests are still available, the next starting point that is yet to appear within the test options is considered. The above processed continues with this state as the initial state, defining the tree for another subspace.

For example, consider the morphological space is represented by three dimensions: the first can be assigned values A, B or C; the second takes values from 1 to 5; the third designated an element from {Δ, Σ, Φ, Ω}. This problem has 60 states within the complete morphological space. Assume this is many more than are able to be tested. Thus, there is a need to consider which states are most valuable to test. Figure 1 shows an indicative DME Tree for this space. Outputs from testing the states have been colour-coded in green, orange and red. For illustrative purposes consider each of these colours to represent the possible outcomes of the test of a given state; green represents pass, red fail and orange partial success. So from the initial state, {A, 2, Φ} if the test is successful the next test state will be {B, 2, Φ}.

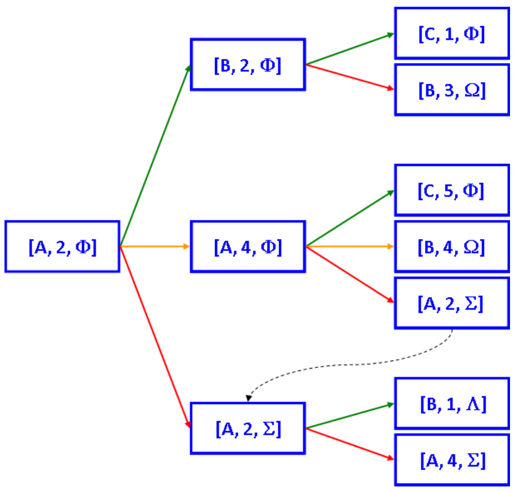


Figure 1: An indicative DME Tree.

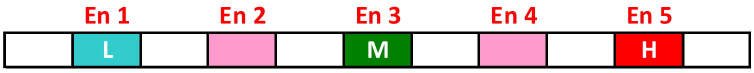
Once the DME Tree(s) has been mapped, the analyst can proceed to traverse the morphological state space in the most efficient and effective way possible.

3. EXAMPLE APPLICATION

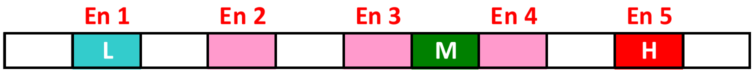
A study has been requested to examine the effectiveness of a mechanised Combat Team (CT) with different combat vehicle variants. The vehicles options considered for this example will be described in terms of forming Light (L), Medium (M) and Heavy (H) CTs. They will be required to face a variety of possible enemy forces, ranging from what is considered to be the easiest (1) to the most dangerous (5). The goal of the study is to determine which types of CTs are capable of defeating which level of opposition.

3.1. Defining the Feasible Scenario Space

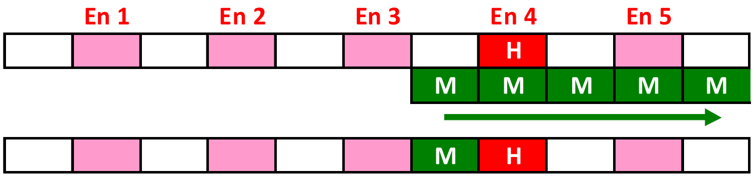
The analysts seek to define the FFSS for each of the three CTs. The above assumption reduces this space to finding the comparable Enemy force. The result of any test can be categorised as a clear dominance of the CT, parity between the forces or clear dominance of the Enemy. For example, if the upper edge of FFSS for the L CT was En 1, for the M CT it was En 3 and for H Ct it was En 5 then this could be represented as a knowledge result of:



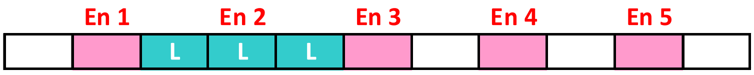
It is possible to fall “in between” the Enemy states. For example, M CT could be stronger than En 3, but weaker than En 4. In this case the FFSS for the M CT would change with the other two remained the same. This would be represented as:



It is given that the FFSS for the L CT < M CT < H CT. Therefore, for example, if FFSS of the H CT = En 4 and FFSS of the M CT > En 3 then M falls between En 3 and 4 as shown below.



The information gained from exploring the state space may only specify a range of possible values a CT may relate to. For example, if L CT > En 1 and L CT < En 3, in the absence of any other testing, then the FSS can only be assumed to rest between En 1 and En 3 as shown below:



It is possible to not be able to differentiate two CTs over specific regions. For example, if L CT > En 1 and M CT < En 4 then all that is known is that the L CT FFSS is greater than En 1 and the M FFSS less than En 4 thus:

In this simplified example, there are 165 unique solution states in the morphological space[1].

To test each of these states it has been determined that a human-in-the-loop wargame is required. Human-in-the-loop wargames require a significant amount of set-up and the analysts only have access to appropriate military participants for a limited time. Thus all states cannot be tested. For this example, consider the case where just four tests can be run; one each day of the experiment.

3.2. DME Tree Approach

Figure 2 gives one possible DME Tree for this problem. On the right of this is the associated knowledge results for each exploration branch.

The Tree used context-specific expertise to determine discrepancies between the presumed understanding of the system and the measured data, as the problem is unwound. Thus, if all CTs are significantly more effective than predicted (reference: top six segments, Figure 2), subsequent tests must adapt and probe in this area.

[1] In a more realistic example this space would be considerably larger, particularly if the different missions types were considered as an additional dimension in the morphological space.

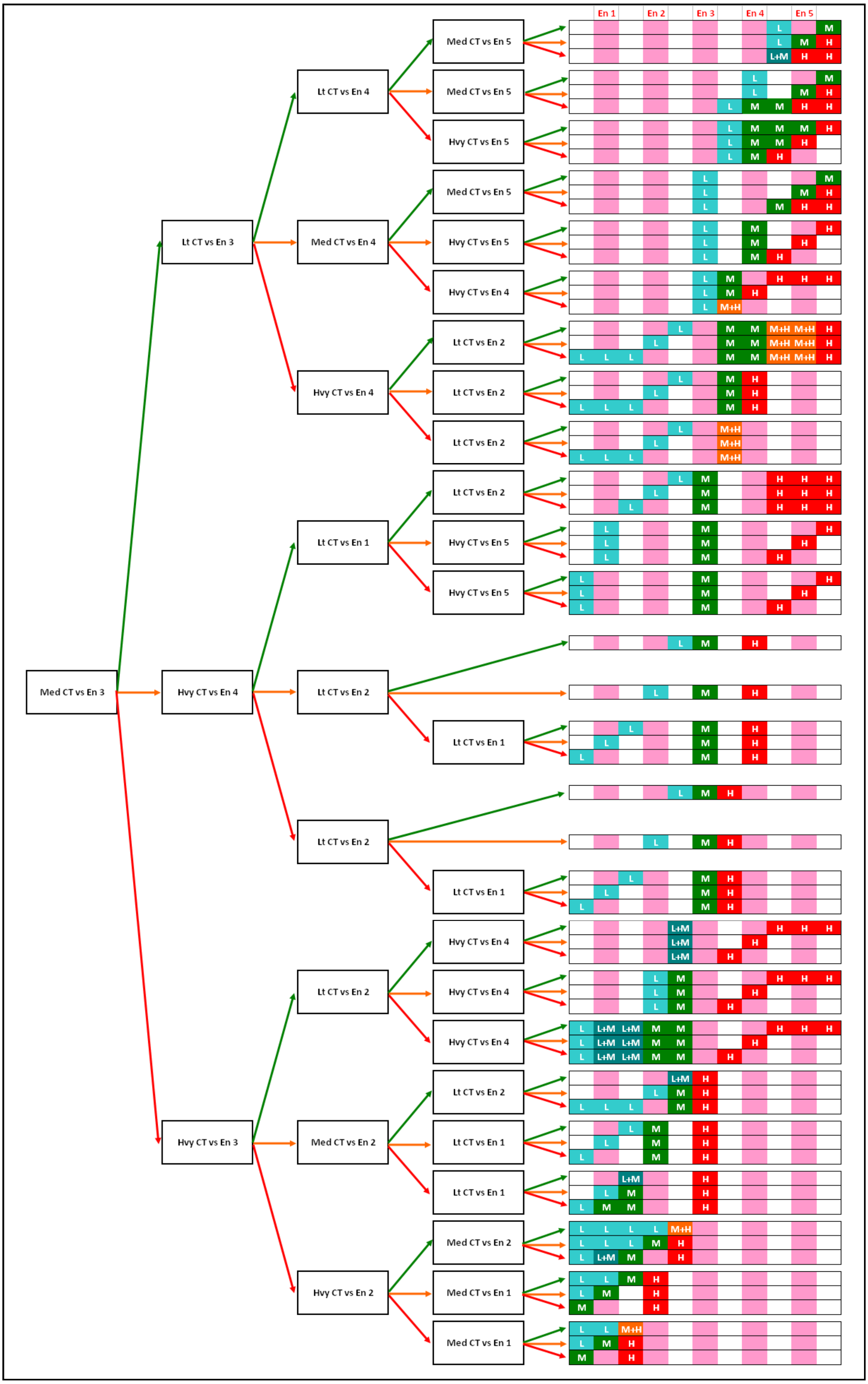


Figure 2: Example Dynamic Morphological Tree with associated Knowledge Results

This Tree only represents one possible solution. There are many more permutations that may be its equal or better. Work has yet to be done to determine methods for optimality structuring DME Trees. This is likely to be specific to the problem being considered.

3.3. High Value States Approach

The key aspect of this dynamic approach involves the analysts, in conjunction with the stakeholder if available, identifying the states to be analysed. In the the High Value States approach the most useful state spaces are identified *a priori* based on existing knowledge of the states and SME advice. In this example, it is determined that based on past studies and experience the Heavy CT will most likely be on par with Enemy 5, Medium with Enemy 3 and Light with Enemy 1. A fourth test run remains, but at this point the choice would be largely based on which of the above 3 options is most likely to be of interest. In this case it is logical that Medium versus Enemy 4 is selected to produce a way-point in case it is too strong for Enemy 3, or if Enemy 5 is too strong for Heavy. This option also provides a realistic most dangerous option for the Medium CT (this approach has strong ties with the approach used within Capability Based Planning (TTCP, 2004)). As a way of getting better coverage of the Morphological space one option is to test Medium CT vs Enemy 4 in one terrain type, Urban say, and test Light vs Enemy 2 in the alternative terrain type Rural.

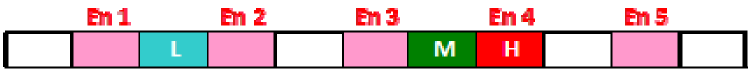
	Enemy 1	Enemy 2	Enemy 3	Enemy 4	Enemy 5
Heavy					X
Medium			X	X	
Light	X				

Figure 3: High Value States run selection

3.4. Comparison of Techniques

To demonstrate the strengths of the method, the High Value States approach can be compared to the DME Tree approach. The output of the methods is a representation of the knowledge gained from executing up to four consecutive tests. In order to compare, a simple metric of how well that knowledge represents the reality is required. To that end, the Certainty Metric is defined as the sums of the number of states for each CT, beyond 1, that the CTs could take.

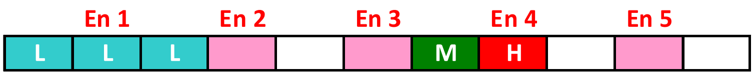
For example, consider the actual state of the system being:



Using the DME Tree in Figure 2:

The first test (Med CT vs En 3) results in success.
The second test (Lt CT vs En 3) results in failure.
The third test (Hvy CT vs En 4) results in parity.
The final test (Lt CT vs En 2) results in failure.

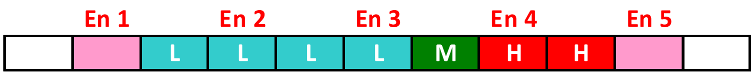
Hence, the outcome of the exploration is that both Med and Hvy CTs are determined correctly, and it is known that Lt falls somewhere below En 2. The Certainty Metric for this outcome is 2.



Using the HVS method in Figure 3:

The first test (Med CT vs En 3) results in success.
The second test (Lt CT vs En 1) results in success.
The third test (Hvy CT vs En 5) results in failure.
The final test (Med CT vs En 4) results in failure.

The outcome of this exploration is that only Med is determined correctly. Hvy could take one of two possible positions, and Lt any of four. This gives a Certainty Metric of 4.



In this particular case, the dynamic exploration resulted in a closer representation of reality than the static a priori test selection. In order to further examine the potential benefits, a simulation was constructed which randomly generated a list of 50 unique ‘solutions’ to the problem. Both methods were applied and the relative Certainty Metrics were compared. It was found that in 39 cases, the DME approach gave equal or better knowledge of the solution.

4. CONCLUSION

General Morphological Analysis is a powerful technique in exploring complex problems. It provides a structured and systematic approach to breaking systems into discrete dimensions, which then form a complete morphological space.

However, even with relatively few dimensions, the size of the morphological space can far exceed the analyst’s ability to exhaustively test each option. They are forced to focus their scope on a subset of the space, and that requires equally complex decision making to ensure the maximum benefit can be gleaned from finite resources.

Dynamic Morphological Exploration is an extension to GMA, which enables the analyst to logically map out an exploration Tree to guide the analysis. The results of each test of the morphological space serve to refine the search patterns for subsequent testing. The impact of this is that large subspaces that are of no consequence can be excised and the critical regions are given the necessary focus.

To demonstrate the strengths of the method, the High Value States approach can be compared to the DME Tree approach.

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