A Multi-Domain Trust Framework for Autonomous Mobile Networks in Harsh Environments

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ABSTRACT

With the increasing application of autonomous, mobile, cyber-physical systems, Trust Management Frameworks (TMFs) are being used to improve the efficiency, security, and reliability of decentralized and distributed autonomous systems. In such systems, subtle misbehaviours can significantly impact the operation and performance of the system as a whole. Techniques have been developed for high-speed, uncontended environments such as terrestrial 802.11 MANETs. However, these do not perform well in sparse / harsh environments such as those found in Underwater Acoustic Networks (UANs), where network nodes experience significant and variable delays, comparatively low data rates, large contention periods, and considerable multi-path artefacts.

In such sparse networks, trust establishment based on statistical observations of success/failure events become unstable and ineffective in detecting or identifying misbehaviours. Additionally, these methodologies focus solely on the communications activities of entities and do not incorporate available information from other domains, such as the physical domain.

In this paper we demonstrate the use and operation of a multi-domain trust management framework (MD-TMF) using UANs as an exemplar application. We demonstrate a methodology that applies Grey Sequence operations and Grey Generators (conceptually analogous to Sequential Bayesian Filtering) to provide continuous trust assessment in a sparse, asynchronous metric space across multiple domains of trust. We also present a machine learning methodology for assessing the relative and collective performance of varying metric sets and subsets in detection and differentiation of a range of communications and physical misbehaviours. *Possibly over-reaching*

Categories and Subject Descriptors

H.4 [**Information Systems Applications**]: Miscellaneous

General Terms

Algorithms Managment Performance Reliability Security

Keywords

MANET, Underwater, Simulation, Trust

1. INTRODUCTION

With the increasing integration of autonomy into modern cyber-physical systems, Trust Management Frameworks (TMFs) are being applied to safeguard the efficiency, security, and reliability of decentralised and distributed autonomous systems, from highway-bound autonomous vehicles to aerial battlefield drones. Classical applications of trust management in Mobile Ad-Hoc Networks (MANETs) have focused solely on observations from the communications domain to make trust assessments. However, these methods are not as effective in applications exhibiting sparse, delayed, or otherwise challenged communications environments[15]. MD-TMF expands the trust management field to include relevant physical factors and movements to increase the threat area protected by the trust framework. An example area of application is the underwater marine environment, where extreme challenges to communications are present (propagation delays, frequency dependent attenuation, fast and slow fading, refractive multi-path distortion, etc.). In addition to the communications challenges, other considerations such as command and control isolation, as well as power and locomotive limitations, drive towards the use of teams of smaller, cheaper, almost disposable autonomous underwater vehicles (AUVs). These increasingly decentralised applications present unique threats against trust management.

In underwater environments, communications is both sparse and noisy. Therefore the observations about the communications processes that are used to generate the trust metrics, occur much less frequently, with much greater error (noise) and delay than is experienced in terrestrial RF MANETS.

Trust Management Frameworks (TMFs) provide information to assist the estimation of future states and actions of nodes within networks. This information is used to optimize the performance of a network against malicious, selfish, or defective misbehaviour by one or more nodes. Previous research has established the advantages of implementing TMFs in 802.11 based MANETs, particularly in terms of preventing selfish operation in collaborative systems [7], and maintaining throughput in the presence of malicious actors [2]. Most current TMFs use a single type of observed action to derive trust values, typically successfully delivered or forwarded packets. These observations then inform future decisions of individual nodes, for example, route selection

[8].

Recent work has demonstrated the use of a number of metrics to form a "vector" of trust. The Multi-parameter Trust Framework for MANETs (MTFM) [5], uses a range of communications metrics beyond packet delivery/loss rate (PLR) to assess trust. This vectorized trust also allows a system to detect and identify the tactics being used to undermine or subvert trust. The authors have previously applied this method to the marine space, comparing against a selection of existing communications TMFs [?] showing that MTFM is more effective at detecting misbehaviours in sparse environments. This paper continues and extends that work to encompass physical as well as communications observations in the establishment of trust and the detection and classification of misbehaviours across both physical and communications domains.
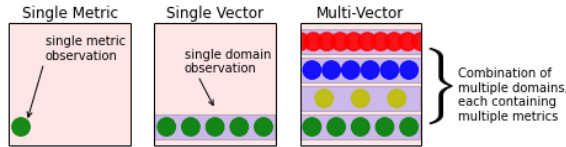
Figure 1: With the addition of further metrics, the threat surface available to an attacker is greatly reduced

This paper is laid out as follows; in section 2 we discuss Trust and TMFs, defining out terminology and reviewing the justifications for the use and development of TMFs in harsh environments such as UANs. In section 3 we review selected features of the underwater communications channel, highlighting particular challenges against terrestrial equivalents. In section 4 we review the findings of [?] and establish experimental parameters and simulated behaviours under assessment. In section 5 we present our analysis pipeline for assessing misbehaviour using MTFM, and intermediate results of the independent detection of physical and communications misbehaviours using single-domain observations. In section 6 we demonstrate results from multi-domain MTFM and discuss the significance of these findings in terms of detection and classification of cross-domain misbehaviour sets.

2. TRUST MANAGEMENT FRAMEWORKS

2.1 Trust in Connected Systems

For a term that is so common in every-day speech, Trust is a challenging discussion area, particularly given the wealth of proposed definitions (Table ??). Beyond these often "fuzzy" definitions, there is a significant ontological conflict between the subjective and objective perspectives of trust; is "trust" an attribute of the actor performing a given action, or of the observer of such an action? Or indeed is trust itself an action upon a relationship between actors? Is it qualitative or quantitative? These questions have challenged philosophers, psychologists and social scientists for decades.

In human trust relationships it is recognized that there can be several domains of Trust for example organizational, sociological, interpersonal, psychological and neurological [?].

In the context of trust between and among collectives of autonomous systems, it is the quantifiable assessment of the expected reliability of an entity to perform a given task on request by another entity. This trust assessment can be targeted towards the reliability of a single task or as a general indicator of "trustworthiness" of a range of activities.

In many systems, this "trust" is analogous to "security", and are often conflated, however in this case we are not necessarily concerned with the security of a system so much as it's runtime reliability in operation.

Within networked systems, the aspect of operation that needs to be protected from malicious operation or failure states is usually bandwidth and congestion, i.e. optimising the network to maximum energy/time efficiency for transiting information. In this respect, the Router Information Protocols (RIP) can be considered very basic Trust Management Frameworks, such that they optimise routing structures within a network based on (binary) link availability.[?].

2.2 Trust in Conventional MANETs

The distributed and dynamic nature of MANETs mean that it is difficult to maintain a trusted third party (TTP) or evidence based trust system such as Certificate Authorities (CA) or Public Key Infrastructure (PKI). Distributed trust management frameworks aim to detect, identify, and mitigate the impacts of malicious actors by distributing per-node assessments and opinions to collectively police behaviour.

Various models and algorithms for describing trust and developing trust management in distributed systems, P2P communities or wireless networks have been considered. *Hermes Trust Establishment Framework* uses a Bayesian Beta function to model per-link Packet Loss Rate (PLR) over time, combining "Trust" and "Confidence of Assessment" into a single value [18]. *Objective Trust Management Framework* (OTMF) builds upon Hermes and distributes node observations across the network [8], however does not appropriately combat multi-node-collusion in the network [3]. *Trust-based Secure Routing* demonstrated an extension to Dynamic Source Routing (DSR), incorporating a Hidden Markov Model of sub-networks, reducing the efficacy of Byzantine attacks such as black-hole routing [12]. *CONFIDANT* presented an approach using a probabilistic estimation of PLR, similar to OTMF, also introducing a topology aware weighting scheme and also weighting trust assessments based on historical experience of the reporter [2]. *Fuzzy Trust-Based Filtering* uses Fuzzy Inference to adapt to malicious recommenders using conditional similarity to classify performance with overlapping fuzzy set membership, filtering assessments across a network [9]. *Multi-parameter Trust Framework for MANETs (MTFM)* uses a number of communications metrics together for form a vector of trust, apply grey information theory to allow a system to detect and identify the tactics being used to undermine or subvert trust[5].

These TMFs (excluding MTFM) can be generalised as single-value estimation based on a binary input state (success or failure of packet delivery) and generating a probabilistic estimation of the future states of that input. These single metric TMFs provide malicious actors with a significant advantage if their activity does not impact that metric.In the case where the attacker can subvert the TMF, the metric under assessment by that TMF does not cover the threat mounted by the attacker. This causes a significant negative effect on the efficiency of the network, as the TMF is assumed to have reduced the possible set of attacks when it has actually made it more advantageous to attack a different part of the networks operation. An example of such

a situation would be in a TMF focused on PLR where an attacker selectively delays packets going through it, reducing overall throughput but not dropping any packets. Such behaviour would not be detected by the TMF.

As an example; The Hermes trust establishment framework [18] uses Bayesian reasoning to generate a posterior distribution function of "belief", or trust, given a sequence of observations of that behaviour, $p(B|O)$(1).

$$p(B|O) = \frac{p(O|B) \times p(B)}{\rho} \qquad (1)$$

Where $p(B)$ is the prior probability density function for the expected normal behaviour, and ρ is a normalising factor. Due to it's flexibility and simplicity, Hermes assumes that $p(B)$ is a Beta function, and therefore the evaluation of this trust assessment is based around the expectation value of the distribution (2) where α and β represent the number of successful and unsuccessful interactions respectively for a particular node i.

A secondary measurement of the confidence factor of the trust assessment t is generated as (3) and these measurements are combined to form a "trustworthiness" value T (4).

$$t_i \rightarrow E[\mathrm{beta}(p|\alpha, \beta)] = \frac{\alpha_i}{\alpha_i + \beta_i} \qquad (2)$$

$$c_i = 1 - \sqrt{\frac{12\alpha_i\beta_i}{(\alpha_i + \beta_i)^2(\alpha_i + \beta_i + 1)}} \qquad (3)$$

$$T_i = 1 - \frac{\sqrt{\frac{(t_i-1)^2}{x^2} + \frac{(c_i-1)^2}{y^2}}}{\sqrt{\frac{1}{x^2} + \frac{1}{y^2}}} \qquad (4)$$

In (4), x and y are constants, used weight the two-dimensional polar mapping of trust and confidence assessments (t_i, c_i), and from [18], are taken as $x = \sqrt{2}, y = \sqrt{9}$.

Upon this per-node assessment methodology, OTMF overlays an observation distribution protocol so as to make the measurements α_i and β_i representative of the direct and 1-hop networks observations of the target node i, as well as expiring old observations from assessment and eliminating observations from "untrustworthy" nodes.

Multi-Parameter Trust Framework for MANETS (MTFM) extends this single-parameter approach, applying Grey Relational Analysis [19] to provide cohort based normalization of a range of disparate metrics at runtime, providing a âĂIJgradeâĂ I of trust compared to other observed nodes, while maintaining the ability to reduce trust valued down to a stable assessment range for decision support without requiring a-priori environmental or metric characterisation. This presents a stark difference between the previously discussed probabilistic approaches. Grey assessments are relative in both fairly and unfairly operating networks. All nodes will receive mid-range trust assessments if there are no malicious actors as there is nothing "bad" to compare against, and variations in assessment will be primarily driven by topological and environmental factors.

Guo et al. [5] demonstrated the ability of grey relational analysis (GRA) [19] to normalise and combine disparate traits of a communications link such as instantaneous throughput, received signal strength, etc. into a grey relational coefficient (GRC), or a "trust vector" in this instance.

The grey relational vector is given as

$$\theta_{k,j}^t = \frac{\min_k |a_{k,j}^t - g_j^t| + \rho \max_k |a_{k,j}^t - g_j^t|}{|a_{k,j}^t - g_j^t| + \rho \max_k |a_{k,j}^t - g_j^t|} \qquad (5)$$

$$\phi_{k,j}^t = \frac{\min_k |a_{k,j}^t - b_j^t| + \rho \max_k |a_{k,j}^t - b_j^t|}{|a_{k,j}^t - b_j^t| + \rho \max_k |a_{k,j}^t - b_j^t|}$$

where $a_{k,j}^t$ is the value of an observed metric x_j for a given node k at time t, ρ is a distinguishing coefficient set to 0.5, g and b are respectively the "good" and "bad" reference metric sequences from $\{a_{k,j}^t k = 1, 2 \ldots K\}$, i.e. $g_j = \max_k(a_{k,j}^t)$, $b_j = \min_k(a_{k,j}^t)$ (where each metric is selected to be monotonically positive for trust assessment, e.g. higher throughput is presumed to be always better).

Weighting can be applied before generating a scalar value (6) allowing the detection and classification of misbehaviours.

$$[\theta_k^t, \phi_k^t] = \left[\sum_{j=0}^M h_j\theta_{k,j}^t, \sum_{j=0}^M h_j\phi_{k,j}^t\right] \qquad (6)$$

Where $H = [h_0 \ldots h_M]$ is a metric weighting vector such that $\sum h_j = 1$, and in unweighted case, $H = [\frac{1}{M}, \frac{1}{M} \ldots \frac{1}{M}]$. θ and ϕ are then scaled to $[0, 1]$ using the mapping $y = 1.5x - 0.5$. To minimise the uncertainties of belonging to either best (g) or worst (b) sequences in (5) the $[\theta, \phi]$ values are reduced into a scalar trust value by $T_k^t = (1 + (\phi_k^t)^2/(\theta_k^t)^2)^{-1}$ [6]. MTFM combines this GRA with a topology-aware weighting scheme (7) and a fuzzy whitenization model (8).

There are three classes of topological trust relationship used; Direct, Recommendation, and Indirect. Where an observing node n_i assesses the trust of another target node, n_j; the Direct relationship is n_i's own observations n_j's behaviour. In the Recommendation case, a node n_k which shares Direct relationships with both n_i and n_j, gives its assessment of n_j to n_i. In the Indirect case, similar to the Recommendation case, the recommender n_k does not have a direct link with the observer n_i but n_k has a Direct link with the target node, n_j. These relationships give node sets, N_R and N_I containing the nodes that have recommendation or indirect, relationships to the observing node respectively.

$$\begin{aligned} T_{i,j}^{MTFM} =& \frac{1}{2} \cdot \max_s\{f_s(T_{i,j})\}T_{i,j} \qquad (7) \\ &+ \frac{1}{2}\frac{2|N_R|}{2|N_R| + |N_I|}\sum_{n \in N_R}\max_s\{f_s(T_{i,n})\}T_{i,n} \\ &+ \frac{1}{2}\frac{|N_I|}{2|N_R| + |N_I|}\sum_{n \in N_I}\max_s\{f_s(T_{i,n})\}T_{i,n} \end{aligned}$$

Where $T_{i,n}$ is the subjective trust assessment of n_i by n_n, and $f_s = [f_1, f_2, f_3]$ given as:

$$\begin{aligned} f_1(x) &= -x + 1 \\ f_2(x) &= \begin{cases} 2x & \text{if } x \leq 0.5 \\ -2x + 2 & \text{if } x > 0.5 \end{cases} \qquad (8) \\ f_3(x) &= x \end{aligned}$$

In the case of the terrestrial communications network used in [5], the observed metric set $X = x_1, \ldots, x_M$ representing the measurements taken by each node of its neighbours at least interval, is defined as $X =$ [packet loss rate, signal strength, data rate, delay, throughput].

Guo et al. demonstrated that when compared against OTMF and Hermes trust assessment, MTFM provided increased variation in trust assessment over time, providing more information about the nodes' behaviours than packet delivery probability alone can. By weighting the metrics used in MTFM it was shown that the trust assessments could be used to identify the style of misbehaviour being performed within the network, and by whom. It has been demonstrated that MTFM is a strong candidate for trust assessment in the harsh marine communications environment [?].

2.3 Multi-Metric Single Domain Trust in Harsh Environments

It has been demonstrated that classical, single metric, MANET Trust Management Frameworks are not directly suitable to the sparse, noisy, and dynamic underwater medium, however MTFM shows promise in it's multi-metric normalisation approach when compared to the performance of OTMF and Hermes in the same scenarios [?]. In a simulated underwater environment, MTFM was able to discriminate between communications behaviours using communications metrics by exploring the metric space by weight variation, allowing the detection and classification of the malicious behaviours. With significant delays (from seconds to many minutes), in a fading, refractive medium with varying propagation characteristics, the environment is not as predictable or performant as classical MANET TMF deployment environments. Without significant adaptation, single metric probabilistic estimation based TMFs are ineffective in such an environment. Existing frameworks are overly optimistic about the nature and stability of the communications channel, and can overlook characteristics that are useful for assessing the behaviour of nodes in the network. This indicates that there is a good case, particularly within constrained MANETs as this for multi-domain trust assessment, where metrics about the communications network and topology are be brought together with information about the physical behaviours and operations of nodes to assess trust.

3. MARINE ACOUSTIC COMMUNICATIONS

The key challenges of underwater acoustic communications are centred around the impact of slow and differential propagation of energy (RF, Optical, Acoustic) through water, and its interfaces with the seabed / air. The resultant challenges include; long propagation delays, significant inter-symbol interference and Doppler spreading, fast and slow fading due to environmental effects (aquatic flora/fauna, surface weather), carrier-frequency dependent signal attenuation, multi-path caused by reflective medium interfaces, variations in propagation speed due to depth dependant effects (salinity, temperature, and pressure), and subsequent refractive spreading and lensing due to that same propagation variation [14].

The attenuation that occurs in an underwater acoustic channel over a distance d for a signal about frequency f in linear power is given as $A_{\text{aco}}(d, f) = A_0 d^k a(f)^d$ and in dB form as;

$$10 \log A_{\text{aco}}(d, f)/A_0 = k \cdot 10 \log d + d \cdot 10 \log a(f) \quad (9)$$

where A_0 is a normalising constant, k is a spreading factor (commonly taken as 1.5 [17]), and $a(f)$ is the absorption coefficient, approximated using Thorp's formula [16]

$$10 \log a(f) = \frac{0.11 \cdot f^2}{1 + f^2} + \frac{44 \cdot f^2}{4100 + f^2} + 2.75 \times 10^{-4} f^2 + 0.003 \quad (10)$$

Refractive lensing and the multi-path nature of the medium result in line of sight propagation being extremely unreliable for estimating distances to targets. The first arriving acoustic signal has as the very least curved in the medium, and commonly has reflected off the surface/seabed before arriving at a receiver, creating secondary paths that are sometimes many times longer than the first arrival path, generating symbol spreading over orders of seconds depending on the ranges and depths involved. Forward Error Correction coding is used on such channels to minimise packet losses.

Comparing $A_{aco}(d, f)$ with the RF Free-Space Path Loss model ($A_{\text{RF}}(d, f) \approx \left(\frac{4\pi df}{c}\right)^2$), the impact of range on signal power is exponential underwater, rather than quadratic in terrestrial RF ($A_{\text{aco}} \propto f^{2d}$ vs $A_{\text{RF}} \propto (df)^2$). While both frequency dependant factors are quadratic, approximating the factors in (10), $f \propto A_{\text{aco}}$ is at least 4 orders of magnitude higher than $f \propto A_{\text{RF}}$

4. ANALYSIS, DESIGN AND PER-DOMAIN RESULTS

4.1 Simulation and Scenario Generation

To investigate the operation of a fully mobile network of six nodes, each kinematically modelled on the REMUS 100 [10] in the marine environment, simulations were conducted using a Python based framework, SimPy [13], with a network stack built upon AUVNetSim [11], using transmission parameters (Table 1) taken from and validated against [17] and [16].

Four misbehaviours were developed to assess both communications and physical misbehaviours *check that we actually talk about misbehaviours before this* such that one node within the fleet was 'misbehaving' (n_m). In cases where n_m is specifically targeting another node in the fleet, that node is denoted as n_t.

1. Malicious Power Control (MPC), where n_m increases its transmit and forwarding power by 20% for all nodes *except* communications from n_t in order to make n_t appear to be selfishly conserving energy to the rest of the team, while n_t itself appears to be performing very well.

2. Selfish Target Selection (STS), where n_m preferentially communicates, forwards and advertises to nodes that are physically close to it in effort to reduce its own power consumption.

3. Shadowing, where n_m is not aware of the pre-planned mission paths and is instead simply following it's neighbours. *This is really bad; this may not apply in this mobility constraint*

4. Slow Coach, where n_m is experiencing a simulated power-train failure that reduces it's acceleration and top speed, analogous to a fouled propeller.

The default scenario is also simulated where nodes participate fairly in the network and follow a collaborative survey mobility pattern.

From these simulations, we attain the per-node recorded positions, ($P_i = [x, y, z]\forall t$) as well as each nodes estimations of it's neighbours positions $P_{i,j} = [x, y, z]\forall t$) (which assumes that all nodes are fairly operating their positions compactly at each transmission), and each nodes trust metric observations of it's neighbours; $A_{i,j}^t = [x_{i,j}\forall x \in X]$ where X are the selected trust metrics.

Table 1: Comparison of system model constraints as applied between Terrestrial and Marine communications

Parameter	Unit	Terrestrial	Marine
Simulated Duration	s	300	18000
Initial Separation	m	100	300
Trust Sampling Period	s	1	600
Simulated Area	km^2	0.7	0.7-4
Transmission Range	km	0.25	1.5
Physical Layer		RF(802.11)	Acoustic
Propagation Speed	m/s	3×10^8	1490
Center Frequency	Hz	2.6×10^9	2×10^4
Bandwidth	Hz	22×10^6	1×10^4
MAC Type		CSMA/DCF	CSMA/CA
Routing Protocol		DSDV	FBR
Max Speed	ms^{-1}	5	1.5
Max Data Rate	bps	5×10^6	≈ 240
Packet Size	bits	4096	9600
Single Message Duration	s	10	32
Single Message Size	bits	10^7	9600

4.2 Communications Trust Metrics

We use the same metrics from [4] that are applicable to the marine environment, i.e. as the simulated modem stack does not operate on the same tiered data-rate approach as used in the 802.11 stack, that metric was not included. Remaining metrics are; Delay, Received and Transmitted power, Received and Transmitted Throughput, and Packet Loss Rate (PLR).

4.3 Behavioural Trust Metrics

Three physical metrics are selected to encompass the relative distributions and activities of nodes within the network; Inter-Node Distance Deviation (INDD), Inter-Node Heading Deviation (INHD), and Node Speed. These metrics encapsulate the relative distributions of position and velocity within the fleet, optimising for the detection of outlying or deviant behaviour within the fleet.

Conceptually, INDD is a measure of the average spacing of an observed node with respect to its neighbours. INHD is a similar approach towards direction orientation.

$$INDD_{i,j} = \frac{|P_j - \sum_x \frac{P_x}{N}|}{\frac{1}{N}\sum_x \sum_y |P_x - P_y|(\forall x \neq y)} \quad (11)$$

$$INHD_{i,j} = \hat{v}|v = V_j - \sum_x \frac{V_x}{N} \quad (12)$$

$$S_{i,j} = |V_j| \quad (13)$$

4.4 Metric Weight Analysis Scheme

From (6), the final trust values arrived at are dependent on both metric values and the weights assigned to each metric. This permits the assessment of the significance of different metrics in the detection and identification of different behaviours. For a metric weight vector H, where the metric m_j is emphasised as being twice as important as the other metrics, we form an initial weighting vector $H' = [h_i...h_M]$ such that $h_i = 1\forall i \neq j; h_j = 2$. We then scale that vector H' such that $\sum H = 1$ by $H = \frac{H'}{\sum H'}$. Using this process we can extract and highlight the primary aspects of an attack by comparing against the deviation from the "fair" result set.

With the nine selected metrics from across communications and physical behaviours, we can explore this metric space by varying the weights associated with each metric, and choose to emphasise across three levels; i.e. metrics can be ignored or over-emphasised. Naively this results in $3^9 = 19683$ combinations, however as these weights are being normalised, duplicates are introduced, e.g. $[0, 0, 0, 0, 1, 0, 0, 0, 0] \equiv [0, 0, 0, 0, 2, 0, 0, 0, 0]$ leaving 18661 unique weights for analysis. As such, re-weighting is applied to each perspective (i.e. observer/target node pair) for each trust assessment time step, presenting 15 perspectives at each step in the 6 node case.

To assess the performance of a given weight combination (i.e. an optimisation factor), we are interested in the metric weight vector that consistently provides the largest deviation in the final trust value T. We approach this as an inverse outlier filtering problem, and select the range outside the $\pm\sigma$ envelope of compared to the equivalent weighting in a known 'fair' behaviour to assess detection (or comparing to other misbehaviours to assess discrimination). Note that at this juncture we are endeavouring to establish "signatures" of different behaviours.

We apply a Random Forest regression [1] to assess the relative importance of the selected metrics on relative detectability of malicious behaviour. Random Forest accomplishes this by generating a large number of random regression trees and prune these trees to fit incoming data. A major advantage of Random Forest in this case is that by walking the most successful regression trees, we can acquire an already normalised maximal activation weight for the particular behaviour comparison being tested.

Using this approach we can explore the results of these simulations.

5. RESULTS AND DISCUSSION

5.1 Per-Domain Analysis

Initially we analyse the per-domain metrics/weight assessments/behaviours before combining the two;

Figure 2: Plot of Comms Metric Feature Extraction

Figure 3: Plot of Behaviour Trust Comparison between Empty, Comms only, and Cross Optimised Signature

THIS IS OUT OF DATE

Centre behaviour is the âĂĲfairâĂĬ case that everything else is being compared against, and is thus, zero, left are

Figure 4: Plot of Behaviour Metric Feature Extraction

Figure 5: Plot of Behaviour Trust Comparison between Empty, Behaviour only, and Cross Optimised Signature

comms behaviours, right are physical behaviours. IâĂŹm working on better ways to present this but basically, each behaviour has a âĂŸsignatureâĂŹ thatâĂŹs fairly clear that maximises the âĂŸoutlierâĂŹ state. In reality, this is maximisation problem, so now that the âĂŸbrute forceâĂŹ case has been worked, thereâĂŹs ample opportunity for putting together a greedy algo to work through these cases in much closer to real time. Depending on how successful my experiments are this weekend, I may slip that into this, or may leave for AAMAS in Nov>

6. CONCLUSION

In this paper we demonstrate that in harsh environments, multi-domain trust assessment can perform better than single-domain counterparts, both in terms of robustness and sensitivity, but also in covering a wider region of the potential behaviour space.

The extension of the methodologies of MTFM into the marine space are already demonstrated, however including information from physical observations of actors in a network enables the detection and identification of a much wider range of behaviours. We also demonstrate a method for assessing trust metrics in harsh environments in terms of their relative significance, and a method for establishing classification signatures for misbehaviours.

It is to be noted that this presented method is significantly more computationally intensive than the relatively simple Hermes / OTMF algorithms communications only algorithms, and is exponential in complexity as metrics and/or domains are added. The repeated metric re-weighting required for real time behaviour detection is therefore an area that requires optimization. More work needs to be done to characterise how worthwhile this approach is compared to a separate synthesis approach where by MTFM-style trust is generated and assessed on a per-domain basis and subsequently fuzed. *This could be just enough to squeeze it in?!*

7. INTRODUCTION

8. TRUST IN MOBILE AUTONOMOUS NETWORKS

8.1 Multi-Metric Trust

8.2 Multi-Domain Trust

9. ASYNCHRONOUS MTFM

10. PERFORMANCE COMPARISON

10.1 Conclusions

Figure 6: Plot of Cross correlation between metrics checking for redundancies

Table 2: Correlation Coefficients between metric weights and behaviour detection targets

Correlation	Delay	P_{RX}	P_{TX}	T_{RX}^P	T_{TX}^P	PLR
Fair / MPC	0.199	0.159	-0.416	0.708	-0.238	-0.401
Fair / STS	0.179	-0.009	0.724	-0.697	-0.145	-0.052
MPC / STS	0.058	-0.134	0.146	-0.768	0.052	0.146

10.2 Acknowledgements

10.3 References

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11. MORE HELP FOR THE HARDY

The aamas2016.cls file is based on the sig-alternate.cls file that is itself chock-full of succinct and helpful comments. If you consider yourself a moderately experienced to expert user of LaTeX, you may find reading it useful but please remember not to change it.

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