Mobility for Trust Assessment in Autonomous Underwater MANETs

Pages: 9, Deadline: 25/3

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***Abstract*—Relevant sections from the CFP art: Key Mgmt & Trust Establishment; Robotic Networks; Vehicular Networks & Protocols; Location Based Services; Mobility Managment**

Do this last

I. Introduction

In the majority of Trusted autonomous mobile network implementations, a free space RF communications protocol such as 802.11 is used as the source of all information about the trustworthy operation of the network. By their nature, such implementations rely on relatively high bandwidth, low noise, low latency, and high channel occupancy where contention is tolerable. In contrast; in underwater environments, communications is sparse, delayful, noisy, and very prone to destructive contention. Therefore, observations of the communications processes used to assess trust occur much less frequently, with much greater error (noise) and delay than is experienced in terrestrial RF MANETS. In addition to the communications challenges, other considerations such as command and control isolation, as well as power and locomotive limitations, and the increasing drive towards the use of teams of smaller, cheaper, almost disposable autonomous underwater vehicles (AUVs), particularly in defense, ecological and petrochemical fields, present unique threats against trust management.

Trust Management Frameworks (TMFs) provide information to assist the estimation of future states and actions of nodes operating as teams, groups or networks. This information is used to optimize the performance of a team against malicious, selfish, or defective misbehaviour by one or more nodes. Previous research has established the advantages of implementing communications-based TMFs in terrestrial, 802.11 based MANETs, particularly in terms of preventing selfish operation in collaborative systems [1], and maintaining throughput in the presence of malicious actors [2]. Most current TMFs use a single type of observed communication action to derive trust assessments, typically successfully delivered or forwarded packets. These observations then inform future decisions of individual nodes, for example, route selection [3].

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) [4], 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. This method as been previously applied to the marine space, comparing against a selection of existing communications TMFs [5] showing that MTFM is more effective at detecting misbehaviours in sparse communications environments.

This paper investigates the application of these communication-based Trust methodologies to the physical domain, to assess the viability of using the motion and mobility of nodes within a team to detect and potentially identify malicious or failing operation within a cohort. This is accomplished by looking specifically at operations within the three dimensions of the underwater space.

In Section II, we review the current applications and mobility patters of collaborative AUV operations, and the current state-of-the-art in underwater localisation techniques. In Section III, we discuss the use of TMFs in the terrestrial space and their applicability to marine operations in general. In Section IV, we design a series of simulations, hypotheses, and tests to assess the detection and identification capabilities of three potential physical metrics for trust assessment.

II. AUV Mobility and Localisation

The use and applications of Autonomous Underwater Vehicles (AUVs) has undergone a great expansion in recent times; current applications and considerations are given in Table I (summarised from [6][**?**]). For the purposes of this exploratory case we do not model the hydrodynamics of the control surfaces of the AUVs, however we do model axial drag as a resistive inertial force.

TABLE I
Applications of AUVs

A. AUV operations and deployments

I have something for this but can't lay my hands on it at the moment; TLDR the used cubic port protection / littoral survey model used isn't perfect but its a reasonable analogue

For Chapter Look at redoing this with other mobilities (particularly distributed lawnmower)

B. Localisation Technologies

Given the subsurface nature of most AUV operations, terrestrial localisation techniques such as GPS are unavailable (below $\approx 20cm$ depth). However, a range of alternative techniques are used to maintain spacial awareness to a high degree of accuracy in the underwater environment.

1) Long baseline (LBL): Long-baseline localisation systems use a series of static surface/cable networked acoustic transponders to provide coordinated beacons and (usually) GPS-backed relative location information to local subsurface users. Such systems can be accurate to less that $0.1m$ or better in ideal deployments and are regularly used in controlled autonomous survey environments such as harbour patrol operations where the deployment area is bounded. However, the initial setup and deployment required in advance of any AUV operation makes LBL difficult to utilise in unbounded or contended areas. LBL systems can also be deployed on mobile surface platforms in the area (ships or buoys for example), but these applications put significant computational pressure on the end-point AUV and have greatly reduced accuracy compared to ideal deployments[7].

2) Doppler Velocity Log (DVL): Doppler logging involves the emission of directed acoustic "pings" that reflect off sea bed/surface interfaces that, when received back on the craft with multi-beam phased array acoustic transducers can measure both the absolute depth/altitude (z-axis) of the craft and through directional Doppler shifting, the relative (xy-translative) motion of the craft since the ping. While classical DVL was highly sensitive to shifting currents in the water column, advances in the development of Acoustic Doppler Current Profiling has turned that situation on it's head, enabling the compensation-for and measurement-of water currents down to the sub-meter level[8].

3) Inertial Navigation Systems (INS): Inertial navigation systems use gyroscopic procession to observe the relative acceleration of a mobile platform. This reference-relative monitoring is particularly useful in the underwater environment, as it detects the motion of AUVs as they are carried by the water itself. Bias Drift is a significant problem for INS systems operating over longer (hundreds of metres) distances, as they usually have some minimal amount of directional bias, that incurs a cumulative effect over time without assistance. Several sensor synthesis processes have been demonstrated which combine information from INS along with DVL data to improve localisation into the sub-decimeter level[6][9].

4) Simultaneous Location and Mapping (SLAM): Simultaneous Location and Mapping is the process of iteratively developing a feature-based model of an environment, and to use the relative movement within that modeled environment to obtain estimates of absolute positioning. SLAM has been most well developed in the contexts of either visual-based inspection using cameras, or LIDAR-style distance triangulation, however the same principles have been successfully applied using marine sonar readings, providing sub-meter accuracy, feature-relative localisation information that is (for the most part) environmentally agnostic[10].

III. Trust Management Frameworks

Trust Management Frameworks (TMFs) are used to improve the efficiency, security, and reliability of decentralized and distributed autonomous systems. 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.[5]

Not sure how much detail to go into in this section; this paper isn't about the formation of trust from metrics, it's about the assessment of metrics at all

IV. Experimental Design

A. Physical 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 of a particular observed node, optimising for the detection of outlying or deviant behaviour within the fleet.

Given that local nodes within the team are aware of the reported positions and velocities of their neighbours, it is believed that this is a reasonable initial set of metrics to establish the usefulness of physical metrics of trust assessment.

Additional metric constructions may be more suitable for certain contexts, platforms or operations, however these were selected in collaboration with UK DSTL and NATO CMRE as suitable, generic, assessments, viable on most current platforms in most current deployment schemes.

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

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

$$INHD_{i,j} = \hat{v} | v = V_j - \sum_x \frac{V_x}{N} \tag{2}$$

$$V_{i,j} = |V_j| \tag{3}$$

Where i and j are indices denoting the current observer node and the current observed node respectively; x is a summation index representing other nodes in the observers region of concern; Pj is the $[x, y, z]$ absolute position of the observed node (relative to some coordinated origin point agreed upon at launch) and Vj is the $[x, y, z]$ velocity of the observed node.

Thus, the metric vector used for the physical-trust assessment from one observer node to a given target node is;

$$X_{i,j} = \{\text{INDD}_{i,j}, \text{INHD}_{i,j}, , V_{i,j}\} \tag{4}$$

At each time-step, each node will have a separate X assessment vector for each node it has observed in that time. Ergo the fleet or team as a whole will have $N \times N$ assessment vectors at each timestep.

B. Physical Misbehaviours

Misbehaviours in the communications space is heavily investigated area in MANETs [11][12][13][14], but attacks and misbehaviours in the physical space are far less explored. Both in terrestrial and underwater contexts, as MANET applications expand and become increasingly *de rigueur*, the impacts of physical or operational misbehaviour become increasingly relevant. As in the communications space, the primary drivers of any "misbehaviour" come under two general categories; selfish operation or malicious subterfuge. Autonomous MANETs in general rely (or are at least, most effective) when all nodes operate fairly, be that in terms of their bandwidth sharing, energy usage, routing optimality or other factors. Physically, if a node is being "selfish", it may preferentially move to the edge of a network to minimise it's dynamic work allocation, or depending on it's intent, may insert itself into the centre of a network to maximise it's ability to capture, monitor, and manipulate traffic going across the network. In the context of a secure operation (or one that's assumed to be secure), the opportunity for capturing a legitimate node and replacing it with a modified clone. Assuming a highly capable outside actor and a multi-channel communications opportunity, there is even the possibility of a node appearing to "play along" with the crowd that occasionally breaks rank to route internal transmissions to a outside agent. In the underwater context this may mean an AUV following the rest of a team along a survey path and occasionally "breaking surface" to communicate to a malicious controller. Alternatively, if an inserted node is not totally aware of a given mission parameter, such as a particular survey or waypointing path, it may simply follow along, hoping not to be noticed.

In all these cases, such behaviour involves some element of behaving differently from the rest of the team, however, there are other cases where such individual "deviance" is observed; where a node is in some kind of mechanical "failure state". In the underwater context, this could be damage to the drive-train or navigation systems, causing it to lag behind or consistently drift off course. An ideal physical trust management system would be able to differentiate between both "malicious" behaviours and "failing" behaviours.

To investigate this hypothesis, we create two "bad" behaviours; one "malicious", where a cloned node is unaware of the missions' survey parameters and attempts to "hide" among the fleet, and a "failing" node, with an impaired drive train, increasing the drag force on the nodes movement. These two behaviours are designated *Shadow* and *SlowCoach* respectively.

C. Simulation Background

Simulations were conducted using a Python based simulation framework, SimPy [15], with a network stack built upon AUVNetSim [16], with transmission parameters taken from and validated against [17] and [18]. For the purposes of this paper, this network is used for the dissemination of node location information, assuming suitable compression of internally assumed location data compressed into one 4096 bit acoustic data frame. Node kinematics are based on REMUS 100 Autonomous Underwater Vehicles, based on limits and core characteristics given in [19], [20] and [21].

These limits are given in Table II

TABLE II
REMUS 100 MOBILITY CONSTRAINTS AS APPLIED IN SIMULATION

Parameter	Unit	Value
Length	m	5.5
Diameter	m	0.5
Mass	kg	37
Max Speed	ms^{-1}	2.5
Cruising Speed	ms^{-1}	1.5
Max X-axis Turn	$^\circ s^{-1}$	4.5
Max Y-axis Turn	$^\circ s^{-1}$	4.5
Max Z-axis Turn	$^\circ s^{-1}$	4.5
Axial Drag Coefficient (c_d)	NA	3
Cross Section Area	m^2	0.13

D. Node Control Modelling

Simple Boidean flocking [22] is used in addition to the guiding Waypointing behaviour to provide a collision-avoidance capability. This consists of three heuristic rules; Cohesion, Repulsion and Alignment, and are shown visually in 1 and mathematically below.

- Cohesion

$$F_{j,C} = F_A \left(p_j, \frac{1}{N} \sum_{\forall i \neq j}^{N} p_i, d_{max} \right) \tag{5}$$

- Repulsion

$$F_{j,R} = \sum_{\forall i \neq j}^{N} F_R \left(p_j, p_i, d_{max} \right) \big| d_{max} > \|p_i - p_j\| \big) \tag{6}$$

- Alignment

$$F_{j,CA} = \frac{1}{N} \cdot \left(\sum_{\forall i \neq j}^{N} \hat{v}_i \right) \tag{7}$$

where F's are force-vectors applied to the internal guidance of the AUV, Where F_A is a scaled vector attraction function, and F_R is an equivalent repulsion function

$$F_A(p^a, p^i) = (\widehat{p^a - p^i}) \times \frac{|p^a - p^i|}{d} \tag{8}$$

$$F_R(p^r, p^i) = (\widehat{p^i - p^r}) \times \frac{|p^r - p^i|}{d} \tag{9}$$

E. Standards of Accuracy

The key question of this paper is to assess the advantages and disadvantages of utilising trust from the physical domain.

It is important to clarify what is meant by "effective" in this case; the "effectiveness" of any trust assessment framework is taken as consisting of several parts.

1) the *accuracy* of detection and identification of a particular misbehaviour
2) the *timeliness* of such detections
3) the *complexity* of such analysis, including any specific training required
4) the *commonality* of the results of any detections between perspectives (also termed "isomorphism" of results)

In this case we are particularly interested in the accuracy of detection and identification of malicious / failing behaviours, and as such are looking at three key characteristics of accuracy; true detection accuracy (what percentage of "bad" behaviours are detected at all); false positive rates (what percentage of "control" behaviours are detected as being "bad"); and misidentification rates (how many instances of one bad behaviour are mischaracterised as the other and vie versa.

As such we have three primary questions to answer to establish if these metrics are useful:

- How accurate are these metrics in being able to easily differentiate between Normal and Abnormal behaviours in terms of True-Positive and False-Positive rates?
- What differentiation of response, if any, is there between the stated abnormal behaviours?
- Can a simple classification be built to characterise these differentiations of response, and what is it's True-Positive/False-Positive accuracy?

F. Analysis Workflow

Having established the metrics under investigation, $MANY$ simluation runs are executed for each scenario (i.e. one node "Maliciously" following the fleet with no mission information, one "Failing" node with simulated drivetrain issues, and one baseline control scenario where all nodes are behaving appropriatly. Eash of these simulated missions last for $duration$, matching realistic deployment times based on current MOD/NATO operations[23][**?**].

1) Metric Cleaning: In order to assess the viability of using the previously discussed metrics for behaviour assessment, the raw motion paths recorded by the simulation are fed into an analysis pipeline[1]. This pipeline initially

[1]We do not currently deal with the case where nodes maliciously "fake" their location

Where i and j are indices denoting the current observer node and the current observed node respectively; x is a summation index representing other nodes in the observers region of concern; X is the vector of metrics from 4; d is an intermediate value of the distance of a given observation from the mean, and α is a resulting normalised response value in terms of it's deviation from the mean.

2) Behaviour Detection and Classification:

This is going to be a bit of a black box while I work out what works automatically; previous versions simply looked at the "Highest Deviator", and while that still works in terms of detection, it's not massively useful in terms of Identification. Could be that in terms of the criteria posed above (simplicity of computation) that using the basic toolkits, we can't do it, however I'd rather not have every single paper I do in my career have half a page explaining the abstract operation of Gray Theory…

One simple behaviour detection is to apply Dixon's Q-test [24] to the resultant $\sum \alpha$ values for each node for each metric for each run a) establish if a "misbheaving node" exists in a given run, and b) identify that misbehaving node.

If you need padding at the end, explain Dixon

For our initial investigation we will use a Confidence Interval of 95%. Our initial hypothesis is that by using observations of the previously stated physical metrics, that we will be able to detect and identify misbehaviours. Within that context, this Confidence Interval indicates that we would expect only a 5% chance that any run or node identified using the Q-test to *not* be a misbehaving run/node.

Further, due to the range of metrics available to us, by applying the Q-test on a per-metric basis, we can use the "votes" of each metric as a simplified consensus classifier.

There's got to be a better phrase than "consensus"…

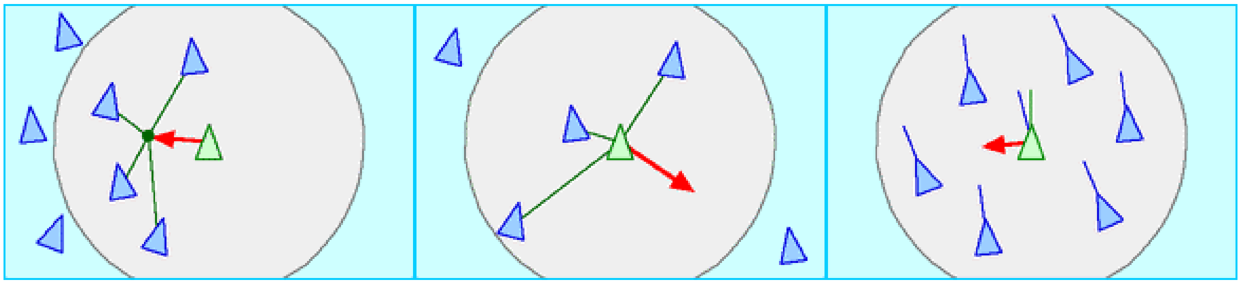
This classifier may allow us to characterise some aspect of a given misbehaviour in terms of metrics it heavily impacts, and those that are less affected.

This can then be augmented by taking the residual deviation of $\sum \alpha_i$ to generate a "confidence" score of a given node being an outlier in a given metric;

$$C_i^m = \Sigma_t \sigma_i^m * \frac{N-1}{\sum_{x \neq i} \Sigma_t \sigma_x^m} \tag{10}$$

3) Operational Performance Metrics:

"How do we measure the impact of a bad-physical-behaviour on the operational success/efficiency of the fleet overall?". We have these numbers already in terms of energy use/efficiency of locomotion, cumulative distance covered, mean time to targets, etc, just need to wrap some words around it



(a) Cohesion (b) Repulsion (c) Alignment

Fig. 1. Visual representation of the basic Boidean collision avoidance rules used

for all m in M **do**
  for all t **do**
    $d_{i,j}^{m,t} = x_{i,j}^{m,t} - \frac{\sum_k x_{i,k}^{m,t}}{|M|}$
    $\alpha_{i,j}^{m,t} = |\frac{d_{i,j}^{m,t}}{\sigma d_{i,j}^{m,t}}|$
  end for
end for

Fig. 2. Numerical Analysis Pipeline for Metric Value Assessment

V. Results and Discussion

A. Detection of Misbehaviours

B. Identification of Misbehaviours

The below table is whats going to be used to condense all the ugly above into something processable across many runs (and most importatly, blind runs)

TABLE III
METRIC CONFIDENCE RESPONSES FOR KNOWN BEHAVIOURS (10)

metric var	INDD	INHD	Speed
Shadow	3.802935	3.191642	1.867909
SlowCoach	4.227141	2.773664	1.509357
Tail	3.874741	3.652717	2.155030
Waypoint	0.920183	0.966642	0.958920

C. Impacts of Misbehaviour on operational performance

VI. Conclusion

In this paper we have demonstrated that with current and on-the-horizon underwater localisation techniques, that in certain mobility models, that a set of relatively simple geometric abstractions (INHD, INDD, and Speed), between nodes as part of an Underwater MANET can be used as a Trust Assessment and Establishment metric.

We show, using a basic cubic survey mobility model built upon a Boidian collision prevention behaviour that in a simulated underwater environment, the outputs of these metrics can be used to detect and differentiate between example malicious behaviour and potential failure states.

This verification further supports the assertions the authors have made previously in [25] that it is practical to extend Trust protocols such as Multi-parameter Trust Framework for MANETS (MTFM)[26] to include metrics and observations from the physical domain as well as those from the communication domain. This combination of physical and "logical" information would further support the decentralised and distributed establishment of observation based Trust, reducing the significant

Acknowledgment

The Authors would like to thank the DSTL/DGA UK/FR PhD Programme for their support during this project, as well as NATO CMRE for their advice and assistance.

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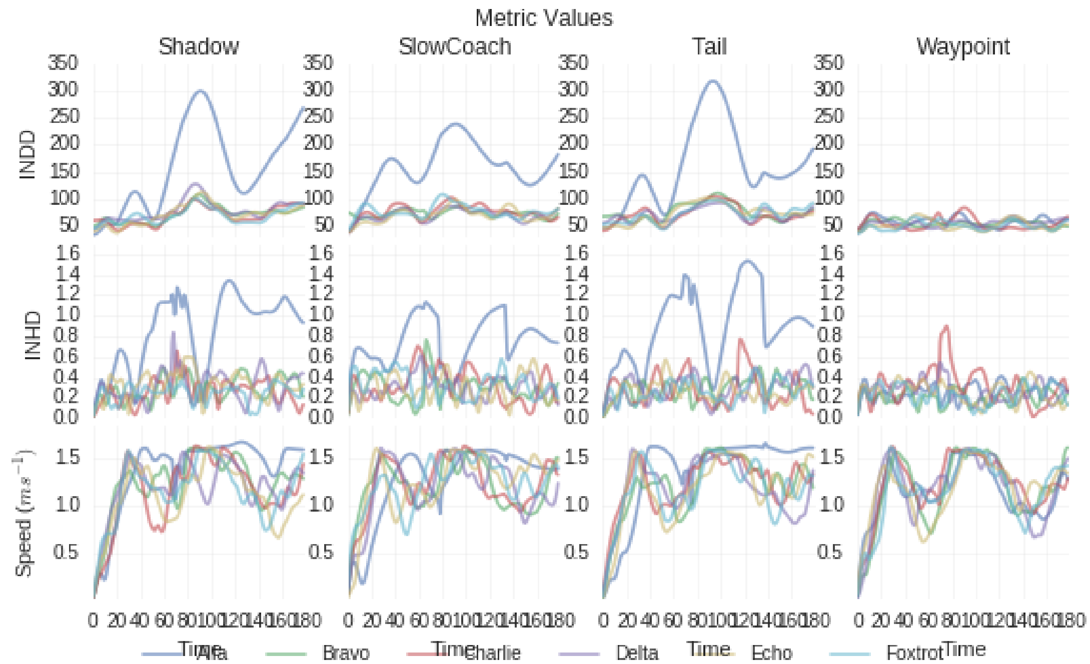

Fig. 3. Observed Metric Values for one simulation of each behaviour ($x_{i,j}^{m,t}$ from Fig. 2)

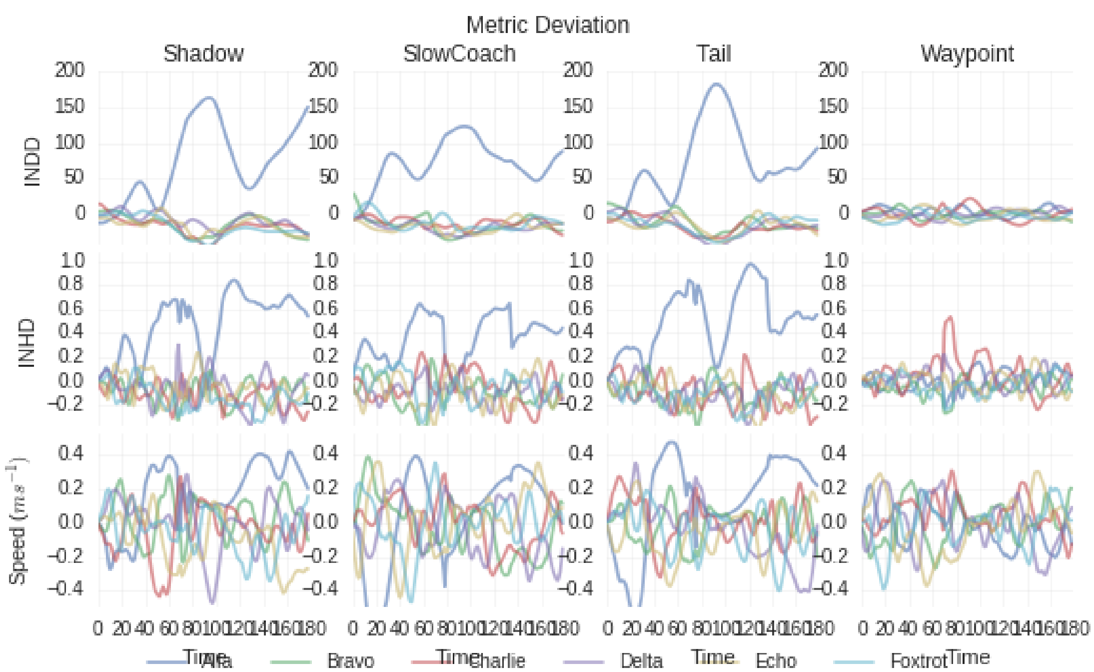

Fig. 4. *Unnecessary but included for draft discussion* Observed Metric Values for one simulation of each behaviour ($d_{i,j}^{m,t}$ from Fig. 2)

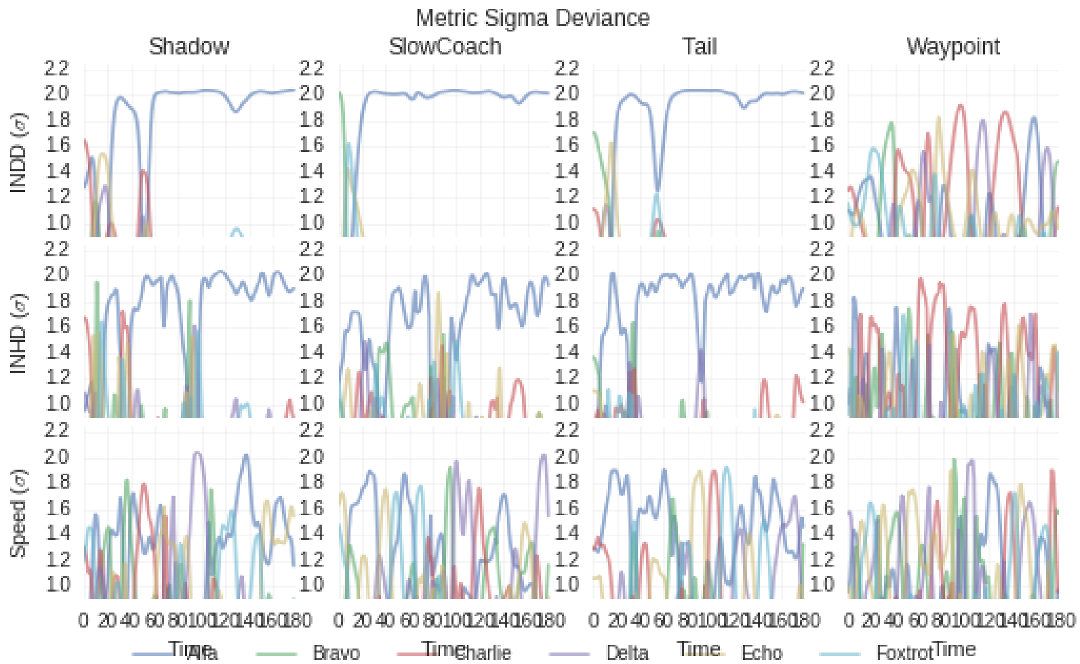

Fig. 5. Observed Metric Values for one simulation of each behaviour ($\alpha_{i,j}^{m,t}$ from Fig. 2)

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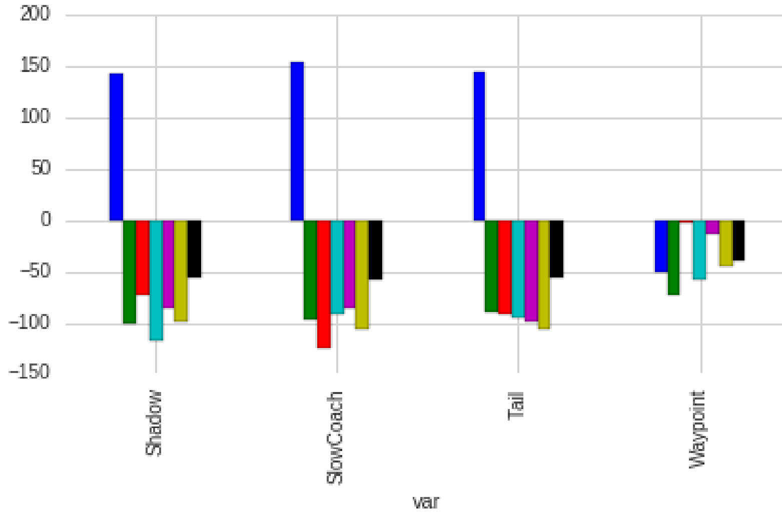
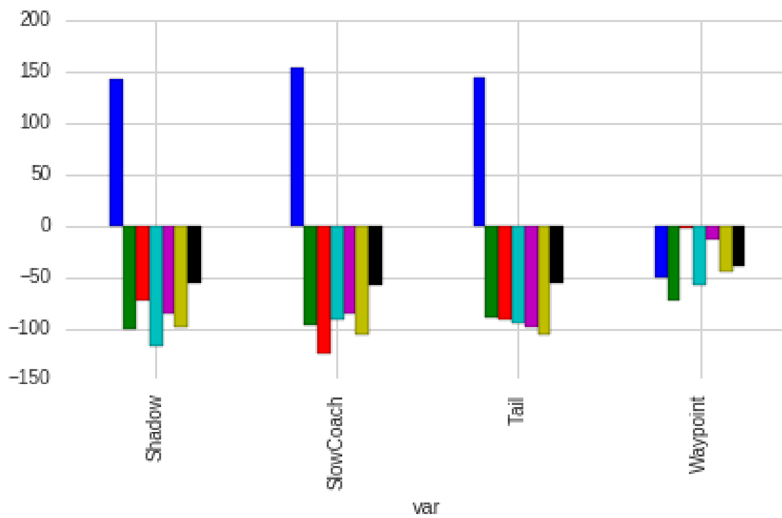
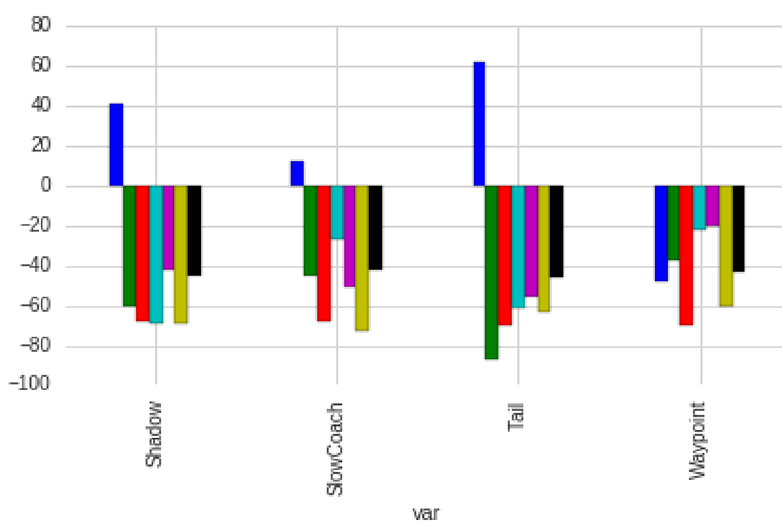


(a) INDD



(b) INHD



(c) Speed

Fig. 6. *VERY Draft; don't get pissy!*: Per-Node-Per-Run $\sum \alpha / T$