Calibrating Trust with Assured Self-Confident Autonomy

Nisar Ahmed
Assistant Professor

Cooperative Human-Robot Intelligence (COHRINT) Laboratory
Department of Aerospace Engineering Sciences
University of Colorado at Boulder

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An Autonomous Robot Appears Before You, and Says…

“Come with me if you want to live…”

What do you do?

Would you **trust** this robot?

What shapes and influences your trust?
Wait – what’s this whole “trust” thing?

Trust = one autonomous agent’s willingness to depend on another

Many mixed contextual influences, including:
• background disposition and beliefs
• look and feel of interaction
• expected vs. actual behavior/capabilities and knowledge (for a robot from future)

→ perceived ability to do what we want and as advertised

What if a robot told you how much it trusted itself to get something done, i.e. its “self-confidence”? (would only an “expert” appreciate this?)

Which of these inspires trust? vs.
Overview

Definitions and User Trust Modeling

– Assurances and actions between user-autonomy

“Self-confidence”

– A possible assurance for calibrating trust

“Trustors/Trustees” for autonomous UXV systems in aerospace

– many conceptual overlaps with social, medical, industrial, etc. robotics
Terminology

• **Trust:** User’s willingness to depend on the autonomous system
  – Depends on situation and initial disposition/beliefs
  – Affects the user’s actions

• **Assurance:** Autonomous system’s ability to affect the user’s trust
  – Positive or negative
  – Can affect trust in several key categories
  – Ultimately affects user’s actions
Barriers to Everyday Acceptance of Sophisticated Autonomy

Some barriers are driven by notion that autonomy must be **type certified**
- Non-Determinism
- Perception / Big Data
- Security / Networked
- Human-UAS Interface
- Modeling and Simulation
- Verification and Validation

Yet, people are **licensed** with relatively sparse assessment
- This is possible because of “trust” of other pilots/users, regulators, societies, etc.
Private Pilot / General Aviation Aircraft

Example: **user** = pilot, **autonomy** = autopilot, **machine** = aircraft

- Autonomy would be type certified
- Regulated by FARs (federal aviation regulations)
  - Pilot is licensed, **autopilot is type certified**, **aircraft is type certified**
Mapping Commercial Farm

Ex: **user** = farmer, **autonomy** = R/C operator, **machine** = aircraft

- Autonomy would be licensed
  - i.e. Driver’s License, Pilot’s License, etc.
- Enabled by Sec 333 / COA (waiver to some FARs)
  - Farmer is unlicensed, **R/C operator is licensed**, **aircraft is type certified**
Pipeline Inspection

Ex: **user** = dispatcher, **autonomy** = path planner + autopilot, **machine** = aircraft

- Assured autonomy requires acceptable human, hardware, software interfaces
- Execution and Algorithmic features would be certified
- Interpreting/Intention Alignment features would be licensed
Pipeline Inspection

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What “Exactly” is Trust?

- Trust is a squishy concept
  - terminology has multiple meanings
  - know it when you see it, but hard to define it
- How do you define in such a way that we can develop design principles for autonomous systems?

- An engineering approach [Lillard, Frew, Argrow, Lawrence, and Ahmed, submitted to IROS 2016]
  - perform literature review
  - apply related work to unmanned aerial systems (UAS)
  - develop a model with clearly defined terms
Literature Review Summary

- Psychology, sociology, business [McKnight and Chervany, 2001], engineering [Lee and See, 2004]

- Literature states that trust is...
  - dynamic
  - multivariate
  - responds to feedback mechanisms
  - should be calibrated, ideally by design

- Our work adds:
  - **Assurances** also multivariate (from different parts of autonomy)
  - Slow outer loop dynamics often ignored
  - Explicit desire to calibrate trust, esp. for non-deterministic behavior
    - Synthesis, not just analysis
  - Multiple overlapped types of trust
    - Trust for customer, trust for operator/pilot, trust for certifier, trust for community/society,...
User Trust Model

Example: Driving Instructor’s Trust in a Student Driver
- User = instructor
- Autonomy = student driver
- Machine = Automobile

Trust - User

- **Faith in Autonomy** – Disposition to generally assume the autonomy is good-willed
- **Trusting Stance** – Disposition that trusting the autonomy will lead to better outcomes

**Example:** The instructor’s disposition that...
- People generally wish to drive safely to avoid possible injury to themselves and others.
- If students are never trusted, cannot fulfill requirements of being an instructor.
**Trust - User**

- **Structural Assurance** – confidence that the *system that supports* the autonomy will promote expected outcomes
- **Normality** – confidence that *operating conditions* will be normal

Example: The instructor’s confidence that...
- The written exam is a good test of knowledge. Traffic lights will function properly.
- The weather appears to be normal and the car is operating correctly.

Relates to support systems (as opposed to specific autonomous system)
Trust - User

- **Benevolence** – Belief that the autonomous system will behave in your best interest
- **Integrity** – Belief that the autonomous system will tell the truth and keep agreements
- **Competence** – Belief that the autonomous system will be able to achieve what is required
- **Predictability** – Belief that the behavior of the autonomous system can be forecasted

Example: The instructor’s belief that...
- The student driver will not intentionally crash the car.
- The student driver has not lied about previous experience and practice.
- The student driver has the motor skills to operate the vehicle.
- The student driver will make similar/repeatable decisions in typical driving scenarios.
Multiple types of assurances


- Focus on **assurances that come from the autonomy**
Implications

- Assumes that: increased trust $\rightarrow$ appropriate use $\rightarrow$ best performance
- Trust only important if it leads to Trust Actions – thoughts are not enough! $\rightarrow$ need interfaces that allow for trust actions
- Assurances are what can be designed
- Feedback loop – assurances from Autonomy to Human – actions from Human to Autonomy
- Dependent of specific application
- Multiple instances of trust for the same system – User, structure, bystander, etc.
Hypothesis

Trust can be **calibrated** by more **insightful assurances about autonomy’s internal processes**

- **What** it’s doing at various levels to interpret human actions, decide on a course of action, implement strategy/tactics/operations/functions

- **Why** it’s doing it or why it’s doing it this way or how clear is it on the situation/objectives/risks

- **How** will it be able to conduct itself to achieve the objective, how experienced/competent/robust is it in this situation
Caveats with “Just” Calibrating Trust

(Amy Pritchett, GA Tech)

– If autonomy is supposedly correct 80% of the predicted use cases, does that mean users should rely on it 80% of the time?

– How does user know whether an immediate case is part of the 80% or 20%?
  • Shouldn’t 100% of cases be seen to see whether the autonomy is correct in *this* case?

– Does user always use same criteria to judge if autonomy is correct?

– Feasible for user to make judgment in situ?

– Even if user believes autonomy to be correct, do other factors impact whether the human relies on it?
  • Ease of doing task oneself, and confidence in ones performance
  • Ease of intervening in automated execution once allowed
  • Responsibility for outcome
Caveats with “Just” Calibrating Trust

• Difference between belief and reliance
  – Reliance involves cost-benefit analysis
• Difference between aggregate performance and confidence in immediate situation.
• Bases in human-human trust (belief):
  – Without frequent interaction: faith
    • Influenced by credentials, recommendations
  – With frequent interaction: perceived dependability and predictability
    • Can be shaped by experience – requires understanding the machine and seeing consistent behavior…
• If a user is responsible for the outcome, (e.g. airline pilot), then her/his job is to “trust, but verify” – can they verify from where they are sitting?
The “Turing Test for Aviation” (Pritchett)

What would one aviation agent expect from another?

- Ability to do a task
- Ability to report when it can’t do a task
- Ability to flex the task structure to achieve desired ends
- Ability to adapt its goals to the situation
- Ability to communicate and coordinate in way that makes sense to other agent
- Ability to ignore other agent when necessary
- Ability to recognize and use interdependencies in inter-agent activities
- Ability to operate at many levels of abstraction simultaneously
Autonomous Agent “Self-Confidence”

Explore machine “self-confidence” (self-trust) as a possible assurance [Sweet, Ahmed, Kuter, and Miller, InfoTech 2015; Hutchins, Cummings, Draper and Hughes, HFES 2015]

• Self-confidence = perceived ability to execute assigned tasks (within defined scope of autonomy), despite uncertainties in…
  – knowledge of world
  – own/self state
  – reasoning process and execution abilities

• How to quantify/qualify?
  – Task competency: boundaries of execution/reasoning?
  – Info adequacy: data sources/models good enough?
  – Communication: how to relate to users?
  – Implementation: how to actually encode in machines?

Come with me if you want to live

Your chances of living are about 73% if you come with me

7 out of the last 10 people who came with me lived

Trust me…
Self-Confidence: Motivation for Definition

• Probabilistic reasoning ubiquitous in autonomy
  – Stochastic models can capture/handle many kinds of uncertainties and nondeterminism

  – …but models are still only approximations of reality
  – …and more approximations needed to solve planning/perception problems
  – What insights to give to users (who are not engineers, statisticians, etc.) on soundness of underlying models, data and decisions?
  – What to do if reasoning/execution competency boundaries reached? How to stay within/away from these? How to know if reached?
Self-Confidence: Implications of Definition

• Machine self-confidence related to, but not same as, uncertainty used for task reasoning
  – One can be certain that probability of success for goal/context pair is 0.02 – and thus be confident of failure
  – One can be very uncertain about the contexts one encounters during plan execution, but confident of robustness with regards to them – and thus be highly confident in face of “known unknowns”

• Self-confidence assessment could be “skewed” if understanding of uncertainty is wrong
e.g. if no/too many “unknown unknowns” assumed
  → over/under confident

• Nevertheless, uncertainty will (and should) tend to undermine self-confidence
A Concrete Application Scenario:
Autonomous Pursuit-Evasion on a Road Network

**Goal:** Autonomous UGV to exit w/o capture
  - **Chaser’s** location and behavior uncertain
  - **Autonomous UAV** gathers info
    - interrogating *unattended ground sensors (UGS)*, taking pictures
    - UGV processes noisy data
    - short-range comm links
  - **Central controller** updates movement/sensing policies for UGV and UAV
    - network represented as finite grid along roads
  - **Remote human analyst** recommends high-level stances to steer planning
    - Operating stance: “get out fast”, “wait and see”, “stay close to safest route,” etc.
    - Enemy’s stance: “trying to ambush”, “searching”, “trying to corner”, etc.
Scenario Features

- Highly complex planning space
  - *suboptimal planning heuristics* practically necessary
  - *no guarantees* that autonomy always “get it right”
  - *human helps narrow down* uncertain decision/info space
  - incentives/rewards can be shaped by human input

- Multiple layers of uncertainty
  - *noisy data* from UGS/camera
  - *models*: true chaser dynamics/behavior unknown
  - “*fog of war*”: limited situational awareness, variety of “actual” operating conditions to piece together

- Strategic high-level interaction with human analyst
  - low-level UAV/UGV autonomy not assessed
  - *self-confidence of central planner as assurance*: feedback to provide better insight into and usage/guidance of autonomous planning
One Possible Diagram for Computing Self-Confidence

User -> Desired Outcome

Command -> Interpreter

Model -> Solver

Plan -> Execution

Execution -> Outcome

Assessment

Past History

Self-Confidence Computation

Self-Confidence

Autonomy
Self-Confidence Factors

\[ X_{sc} = [x_1, x_2, x_3, x_4, x_5, \ldots] \]

- **\( x_1 \)** Command Interpretation
  - are autonomy and user ‘on the same page’?
- **\( x_2 \)** Model Validity
  - how well does autonomy’s model reflect reality?
- **\( x_3 \)** Solver Quality
  - how well can the solver use the model to generate policies/plans?
- **\( x_4 \)** Outcome Assessment
  - how ‘good’ is expected distribution of results?
- **\( x_5 \)** Past Performance
  - how well has the autonomy done in similar circumstances?
Some Other Recent Related Algorithmic Work

- Qualitative visualization of plan/sensor-related uncertainties
  [Hutchins, Cummings, Draper and Hughes, HFES 2015]

- Counter-planning for self-assessment and plan repair
  [Kuter and Miller, AAAI FS 2015]

- Statistical model residuals for object recognition in robotic sorting
  [Kaipa, Kankanhalli-Nagendra, and Gupta, AAAI FS 2015]

- Surprise index for assessing Bayesian network models
  [Zagorecki, Kosniewski, and Drudzdel, AAAI FS 2015]

For more:
see AAAI 2015 Fall Symposium on Self-Confidence in Autonomous Systems:
[scas2015.recuv.org](http://scas2015.recuv.org)
(proceedings available at [https://www.aaai.org/Press/Reports/Symposia/Fall/fall-reports.php](https://www.aaai.org/Press/Reports/Symposia/Fall/fall-reports.php))
Conclusions

Trust = willingness of one autonomous agent to depend on another
   – something to be calibrated to appropriate level

User trust model: engineering perspective and attempt to develop autonomous system design principles from UXV perspective
   – assurances and trust actions: key “input/output signals” of trust
   – online/offline flavors: live interaction, certification, etc.

Machine self-confidence: possible assurance for calibrating trust
   – introspective self-reporting of “competency boundaries”
   – wide open -- a possible basis for licensing sophisticated “everyday” autonomy?
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