Using a self-confidence measure for a system-initiated switch between autonomy modes

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Abstract

This paper presents preliminary results of the ongoing project RIMRES – Reconfigurable Integrated Multi-Robot Exploration System[1]. The paper outlines the concept of a novel approach for realising sliding autonomy with a mixed team of humans and robots. In order to increase the overall team efficiency, a formalised trust based relationship between operator and system is suggested, allowing a robotic system to use a self-confidence measure to actively control its autonomy mode. This paper provides a survey on the current state of the art in the relevant field and gives an outline of the developed concept and its motivation. To support the understanding of the concept initial experimental results are presented, followed by a discussion of the concept.

1 Introduction

Robots are nowadays used in a variety of applications ranging from lawn cutting to exploring extraterrestrial environments. The application of robots is most often triggered by efficiency reasons and thus much research is put into developing reliable and autonomously operating robots. However, with a broad range of applications, yet no robot with overall human-like capabilities has surfaced, but most often robots are specialized for a selected set of tasks. While some robots will operate fully autonomously within this set of task, many others will be usually operating on a scale between fully autonomous and manually controlled by an operator. The reasons lie in minimizing associated risks, i.e. harming humans, damaging property or loosing the robot itself, and originate from a lack of technological abilities and limit of trust into autonomously operating systems. This lack of trust into automation is even bigger, when there is a direct comparison to human performance, while it will be far less for industrial applications which focus on speed and accuracy far out of reach for human performance.

For robot operations at remote, previously inaccessible or even hazardous locations the highest risk associated comes with the loss of the robot itself. Thus, such operations follow a rather conservative approach of controlling robots, meaning a stronger tendency towards manual control. Commonly, this will mean that a mixed team of humans and robots perform such missions. For many mixed teams an efficient execution of the overall mission is essential and becomes even more important when deploying a multi-robot system.

Multi-robot systems can be applied in a variety of ways: be it as a collection of simple, but homogeneously designed robots in swarms or as small teams of heterogeneous robots each designed to perform a specific task. For most applications of multi-robot systems at least one system operator will be necessary to monitor task execution. However, the risk of loosing the device and any directly associated costs vary independently, e.g. loosing a single member of a robotic swarm with greater than 100 homogeneous devices versus loosing a member of a small robotic team with about five members which have unique capabilities. To reduce the risk, a ratio of 1:1 between the number of operators and number of robots does provide a possible solution, but requires additional organization and communication strategies. Therefore an efficient solution to mixed team control is required.

The development of an efficient team control for a small team of robots is part of the project RIMRES. This robotic team consists of two main robot types: a rover and a scout. One of the main features of the team is its flexibility of combining functionality: the rover and the scout can act as a single functional unit, i.e. combined they actually represent a third main type of robot. In addition, standardized modular components allow the dynamic creation of further team members, e.g. by combining a battery module with a payload module, or they add functionality to rover or scout. All team members will also be able to perform autonomous operations such as executing scientific experiments.

[1]The project is funded by the German Space Agency (DLR), Grant No. 50 RA 0904. RIMRES is a cooperation between the DFKI Bremen - Robotics Innovation Center and ZARM - Center of Applied Space Technology and Microgravity

The project RIMRES evaluates the application of this team for deployment on the lunar surface. The robotic team is supported by ground operators. While there is only one physical rover and scout in RIMRES, the project also supports the deployment of a larger team of robots. The number of main robots and modular components therefore requires to find a control mechanism that optimises the efficiency of the anticipated mixed human-robot team.

Different concepts already exist to control robots embedded in mixed human-robot teams. The field of sliding autonomy [12] also known as adaptive/adjustable autonomy and mixed initiative control is one area that has been focusing on this topic. Its central motivation of research is increasing the efficiency of mixed teams by adjusting the autonomy level of individual robots. In this paper, we want to present a novel approach to allow optimisation of a system's autonomy and mixed initiative control. This approach is based on a trust based relationship between operator and system, eventually allowing the system to use a self-confidence measure to actively control its level of autonomy.

This paper is structured as follows. We highlight the state of the art in the relevant areas of our approach in Section 2. Our concept is described in Section 3. Initial experiments to illustrate elements of the concept have been performed and are presented in Section 4. Eventually, we discuss our approach in Section 5, and conclude as well as give an outlook in Section 6.

2 Background and Related Work

The following three sections will highlight the state of the art in the relevant areas for our approach: definition of autonomy levels, concepts for sliding autonomy, and trust in automation.

2.1 Autonomy and autonomy levels

Definitions of individual levels of autonomy are commonly used to describe the capabilities of an autonomously operating system. Many approaches define a discrete set of autonomy levels, though Parasuraman et al. [20] stress, that the level of automation lies on a continuous scale between fully manual and fully autonomous operation as. Often these discrete level definitions refer to the known ten point scale of Sheridan and Verplank [22]. Sheridan and Verplank advocated a set of ten discrete autonomy levels early on, using generic behaviours to define each level, e.g. operating with an autonomy level of six allows a human a restricted time to veto against the automatic action of a system. Here, levels mainly refer to the source of initiative for requesting information or making a decision. In [20], Parasuraman et al. extend the initial approach of Sheridan and Verplank to a four-stage model of human information processing consisting of an automation level for information acquisition, information analysis, decision selection and action implementation each, but stress the need for empirical evaluation for level of autonomy especially for information acquisition and analysis. Such evaluation can be found in [7][8], where Fereidunian et al. confirm the need for different autonomy levels for each dimension.

Given a discrete set of autonomy levels, many researchers use a context specific selection of dimensions and levels. For example, Dorais et al. [5] consider the following aspects: (1) task complexity, (2) number of subsystems, (3) situations when systems override manual control, and (4) duration of autonomous operation. The US National Institute of Standards and Technology (NIST) specifically addressed this issue and hosts an open work group called ALFUS (Autonomy Levels For Unmanned Systems), though seemingly inactive since 2008. The aim of this group is to define autonomy 'from remote control to full and intelligent autonomy' in a metric based system (again on a scale of zero to ten). NIST considers three dimensions to define autonomy levels: (1) mission complexity, (2) one of: human/operator independence, or autonomy level and (3) environmental complexity. Here, the highest autonomy level offers independent actions in extreme environments. In contrast, Sholes [23] considers another four specific dimensions for autonomy: environment observation, orientation, decision making and action taking. He also uses ten autonomy levels, but in combinations with the dimensions it leads to a four by ten autonomy control level matrix (ACLs). For each element of the matrix he provides a detailed description of capabilities.

Another evaluation for autonomy levels lies in contrast to the previously described ones and is given by Huber [13]. From his point of view a robot's level of autonomy depends on the robot's sensitivity to external, possibly negative influences that try to corrupt the robot and stand in contrast to resource dependencies that might arise in multi-robot scenarios. To define an autonomy level a single value computed as a weighted sum of two other parameters representing social integrity and social dependencies. The value representing social integrity is based on the analysis of the robot internal flow of information. Huber assumes that passing information through different reasoning layers removes external influences. Thus, social integrity is a more or less predefined characteristic of an individual robotic system, since it depends only on internal information processing structures (path of influence). As such social integrity quantifies the 'weakness' of an agent toward outer influences. In contrast, social dependency can vary throughout a task given changing (social) dependencies among agents.

2.2 Switching between autonomy levels

It is essential to understand the meaning of autonomy and autonomy levels. However, concepts for switching between autonomy levels are part of sliding autonomy research and try to develop concepts for the efficient use of the existing autonomy levels. An overall approach of using sliding autonomy is shown in [21]. Sellner et al. address the challenge of defining sliding autonomy for multi-agent systems and identify three critical factors: (1) a robot's ability to request help, (2) an operator's situational awareness (also stressed by Whitlow and Dorneich [25]) once a robot requires help and (3) coordination of the whole team, when an individual robot is controlled manually. Their basic assumption is that automation serves to maximise the team efficiency and they increase the success rate of team operations by embedding a prediction for task duration and success (or failure). They use empirical data for each task to compute priors for autonomous operation and operator controlled execution, and embed this concept into the more generic approach of proactive planning. They use two specific modes defined by Heger and Singh [12]: (1) System-Initiative Sliding Autonomy (SISA), where robots request help from the operator, and (2) Mixed-Initiative Sliding Autonomy (MISA), where the operator constantly monitors progress and interferes if required.

In many applications, system-initiative becomes an important factor and Baker and Yanco [1] show that even though switching autonomy levels can lead to higher efficiency, requiring an operator to actively switch between autonomy levels leads to poor performances. The process of gaining situation awareness distracts operator from its original task, and they tackle this problem by embedding an algorithm to suggest to the operator when to switch the autonomy level. Meanwhile, a variety of system-initiative procedures have been developed. While using system-initiative to trigger a scientific search [6] is a rather simple example, Kaupp and Makarenko [15] use a decision theoretic approach and include humans as a resource for robots. They consider different sources of information, and estimate the benefit of including information from other sources into a future decision. Thus, whether an operator has to be involved in a robotic action or not depends only on usefulness and the autonomy level is eventually reflected by the frequency of requesting information. In comparison Machinetta aka Multiagent Adjustable Autonomy Framework (MAAF) [10] uses a decision-maker hierarchy and delegates control to a capable decision-maker at the time and follows a predefined escalation sequence to do so. Decisions are forwarded until a capable decision-maker be it human or robot has been found, though Freedy et al. do not not clarify in this paper, what the constraints are in order to be capable of making a decision.

2.3 Trust in automation

In most autonomy concepts the factor trust is only represented implicitly - by allowing a robot to act autonomously one trusts the robot to be capable of performing actions without supervision. Nevertheless, various studies relating trust in automation have been performed within the field of human factor research: Lee and Moray [18][17] investigate on the development of human trust into automation, while Freedy et al. [9] try to give a rational and analytical founded trust model [2] [16]. A good general discussion of trust is provided by Madhavan and Wiegmann [19], and showing that trust in automation does reflect multiple factors ranging from self-confidence of the operator to the perceived experience with a system and thus reduces a complex situation initially to a rather fuzzy description.

Blomquist [2] provides a collection of references to social psychology that also holds for mixed human-robot teams. First of all, trust comes with some information and risk, since complete knowledge makes trusting obsolete, while no knowledge does not give any grounds for trust. Furthermore, trust requires belief into trustworthiness of the counterpart and the consequence of the trusting person (or system) to rely on it. Blomquist also acknowledges that trust will be situation-specific and presents multiple definitions of trust which vary throughout the fields of philosophers, social psychologists, economists and more.

A first approach of modelling trust is presented by Freedy et al. [9] who use a relative expected loss function which weights the actual observed risk of a faulty operation against the number of operator overrides.

3 Concept

The following sections outline the motivation for our concept and the essential elements of the concept itself: measure of trust, measure of self-confidence, and the design of the system-initiated switch.

3.1 Motivation

It can be seen from the current state of the art, that there are two complementary but insufficiently answered questions: (1) when to automate, and (2) when not to automate. While (1) comes with a preference for manual operation and mistrust into automation, (2) assumes initial full trust in automation with a need to limit this trust in specific situation.

In our assumption we naturally thrive for maximising automation. However, maximising automation does not mean to automate at all cost, but automating tasks so that: (1) the overall (mixed) team efficiency increases and (2) that the goal is being achieving with an equal or better result compared to a lesser degree of automation.

Similar to Heger and Singh [12], we aim at a combined SISA/MISA mode which we redefine as mixed-initiative mode. This takes into consideration their observation that choosing between SISA and MISA does not make a big difference regarding efficiency, but that a human's attention does. In addition, many other authors [4][5][21][24] have stressed the general importance of situation awareness for mixed human-robot teams as well. However, we have to consider the finding of Baker and Yanco [1] and focus on the system-initiative. Thus, we will aim at using three main modes: (1) manual mode, (2) mixed-initiative mode, and (3) (full) autonomous mode. We also use three switching types: (1) preassigned switch, (2) human-initiated switch and (3) robot-initiated switch. The types have been already mentioned by Brookshire [3] and Figure 1 illustrates their meaning for a task performed by a mixed team.

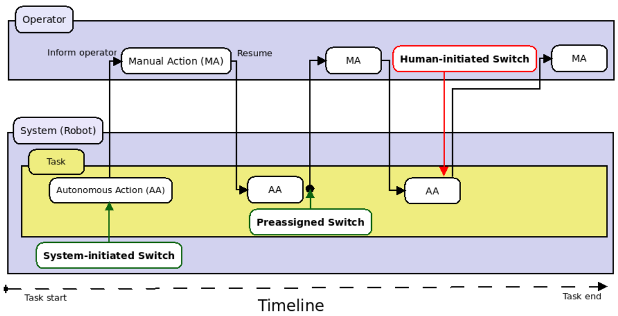

Figure 1. Interaction methods for a mixed team

The mixed-initiative mode lies at the centre of attention, so that we aim at system-initiated switching between autonomy levels, but also having one or more operators, which are responsible for monitoring multiple systems. We assume that each robot has an optimal setting of its autonomy mode, were it maximises the team efficiency, i.e. operating in a safe, autonomous manner, and requesting help when needed. Efficiency can be measured using a cost function, which depends on following parameters: risk of loosing the robot, costs of replacing the robot, number of operator interactions, number of human-initiated switches, severity of the switching reason, amount of time required for human-interactions, and the success of the operation. Thus, we have to maintain a high reliability, while minimizing human-interactions and especially human-initiated switches, since they indicate problems the robot could not even identify.

While a broad range of application and device specific autonomy levels exist, we will try to achieve an implicit definition of the autonomy level. The level of autonomy should directly depend on the amount of external support a system requires. In our scenario, the autonomy level has therefore to reflect the dependency on human intervention.

Our reasoning for embedding a trust relationship with Good's [11] definition of trust, which fits our situation best:

> "Trust is based on an individual's theory as to how another person will perform on some future occasion, as a function of that target person's current and previous claims, either implicit or explicit, as to how they will behave."

Similarly, Madhavan and Wiegemanns [19] describe trust being based on predictability and consistency, and also consider dependability, i.e. here a system's level of confidence in the operator. However, in our concept we neglect dependability and assume a well trained operator.

3.2 A measure of trust and building trust

How much an operator can trust a robot, depends on factors such as general knowledge about the robot's capabilities, information about the current state of the robot, experience how the robot performed in the past, information about the environment, and the task to perform. Trust in our context will be (initially) simplified and equivalent to the reliability of a robots performance on a specific task (Parasuraman et. al. [20] already note that a consideration of reliability only is not sufficient). We assume that robots before being capable of performing a mission have to be trained - similarly to human participants. This training generates the necessary experience with the robot and eventually defines the level of trust. Operator trust will then correspond to the likelihood of success given a specific autonomy level. Since the computation of trust requires experience, we require a minimum number of samples in the database and embed a weighting with a trust prior:

$$\tau(\alpha) = wP(S|\zeta, \alpha) + (1 - w)P(S) \tag{1}$$

τ	trust function
α	autonomy level
w	weight, as $\min\left(1, \frac{\#\{number\ of\ samples\}}{\#\{minimum\ required\ samples\}}\right)$
$P(S)$	prior probability of success
ζ	command and environment parameters

Trust will directly correspond to an autonomy level, but it can be claimed that changing the autonomy level creates a number of new unknowns and thus requires to reset the level of trust to a prior value. Changing to a higher autonomy level requires experience. Thus, we will use the trust associated with the preceeding, lower level of autonomy as a prior value and apply the same weighting function given by Equation 1.

Thus during the training phase the operator (or even the system itself) will gain trust for each autonomy level and will successively be able to increase the autonomy level, until performance of the robot starts to deteriorate. The number of human-initiated switches serves as an indicator for performance deteriorization. Ideally, this process allows a convergence to the maximum autonomy level for a specific task.

3.3 A measure for self-confidence

As a counterpart to the operator's trust, the robot's self-estimation is the essential parameter to switch between the autonomy modes. This self-estimation lies combined in another scalar: a self-confidence measure that provides the robot's estimation of being able to succeed on a given task. This follows Blomqvist [2] interpretation of confidence: 'The actor expects something to happen with certainty, and does not consider the possibility of anything going wrong'. Thus, confidence can be understood as an estimation of the probability of successfully completing a task given all current information. This estimation represents an essential part of our concept.

Our concept models self-confidence as an estimation of future performance based on: (1) experience, (2) current state of the robot and (3) current task state. Experience of a robot can be analysed upon success given influencing factors such as operation environment, command parameters and system state at that time. In order to estimate the current state of the robot, system diagnostics are essential. These diagnostics have to reflect the state of the hardware that is relevant for the specific task, i.e. battery status, the existence of a specific modular component, and the available computational capabilities of the robot. Jakimovski and Maehle[14] show an approach using Artificial Immune Systems to compute such a single diagnostic value, which they call anomaly value. However, diagnostics also have to embed a healthy software state, e.g. evaluate the working of required software components. For these diagnostics, the current state of the task can be measured using heuristics that initially compensate for missing experience or later condense existing experience, and rules to embed constraints and explicit knowledge. In Section 4 we will give an example of such confidence computation.

3.4 System-initiated switch between autonomy levels

We start with a simple definition for a system-initiated switch which is defined using the trust of the operator τ and the robot's (self-)confidence κ, which are both normalised scalar values. Any autonomous operation of the robot requires that the relation defined by Inequality 2 is fulfilled.

$$\kappa > 1.0 - \tau \tag{2}$$

This allows the following options for highest and lowest autonomy mode: (1) manual control when trust $\tau = 0.0$, and (2) fully autonomous mode when trust $\tau = 1.0$. The mixed-initiative mode is active as long a $0.0 < \tau < 1.0$ and $\kappa > 0$. While τ is constant over a single task execution, κ will change dynamically during task execution. The active autonomy level of a system will be equal to the trust put into the system, thus the current level of trust and the autonomy level are interchangeable. This approach allows an intuitive interpretation, since a system can only operate autonomously when being trusted and while having (sufficient) self-confidence of success.

4 Experiments

To illustrate the concept outlined in the previous section, we developed a simulation that embeds a model for a human operator, the self-confidence of the autonomously operating system and an optimisation strategy for finding the optimal autonomy mode for a system. The model of the robot's confidence embeds randomly occurring events that reduce the self-confidence significantly, eventually leading to a switch between autonomy modes. Reliability or rather trust is the probability of success:

$$P(S) = \frac{\#\{number\ of\ successful\ task\ executions\}}{\#\{number\ of\ task\ executions\}} \tag{3}$$

Figure 2 illustrates the switching between autonomy modes. While the self-confidence will be greater than 0.9 in a normal situation, the system initiates an autonomy mode switch, i.e. requesting operator help, as soon as the confidence drops below the threshold which is defined by the autonomy level. The user interaction time is modelled using a normal distribution with a mean of 60 s and a standard deviation of 20 s. We modelled a probability of 10% that an operator's intervention might not lead to the given success, e.g. in Figure 2 a human interaction after around 500 seconds of task execution does not lead to an increase in the system's self confidence. Instead, the system switches back to manual mode since the situation did not improve after the operator's intervention. Thus, our concept provides an implicit control of any human intervention.

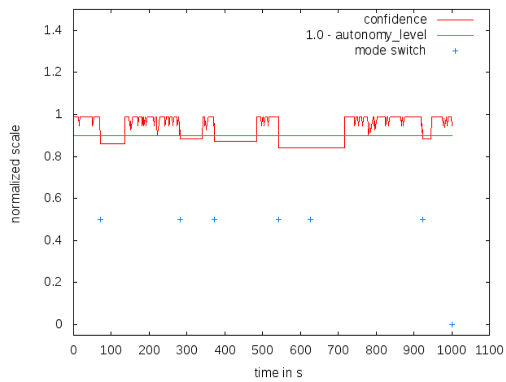

Figure 2. System initiated switching

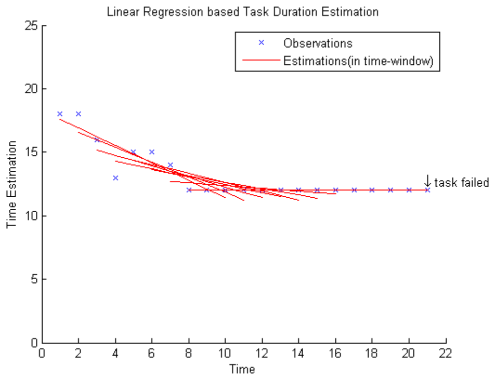

Figure 3. Online estimation of the task duration

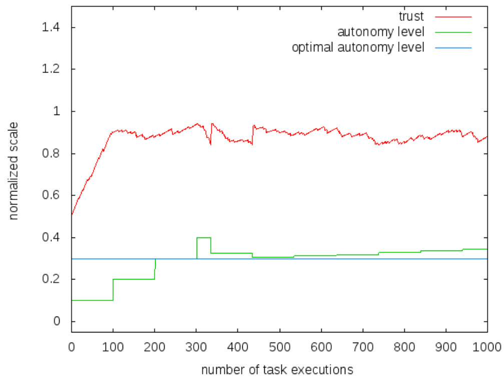

Figure 4. Optimisation of the autonomy level

Estimation of the task progress is an influencing factor for the system's self-confidence. Figure 3 illustrates the application of a heuristic in order to support the computation task progress. Here, we selected the typical robotic task 'navigation'. For navigation the self-confidence measure has to be reduced: (a) when a path to the next waypoint cannot not be found, (b) a computed path cannot be followed. We allow for an online estimation of the task duration based on the left distance to the target. By applying a least-square estimation over previous observations, the gradient can be the basis for influencing the self-confidence in an anti proportional manner.

As already mentioned in Section 3 multiple assumption can be made regarding the level of trust after changing the autonomy level. For an unknown system we start with a prior trust of 0.5. Figure 4 illustrates an optimisation process, where the trust value of previous performances that led to an increase of the autonomy level serves as a prior. Switching to a higher autonomy level (as mentioned, trust level and autonomy level are interchangeable) will only be allowed, when the minimum required experience of 100 task executions has been gained along with a reliability of at least 80% (trust = 0.8). Any deterioration of the reliability requires a correction of the autonomy level. Here, we assume a failure rate of 10% and increase this rate linearly with the distance of the current to the optimal autonomy level. Since we allow for additional errors by requiring only low reliability, the autonomy level is optimised to meet this reliability and thus deviates from the autonomy level that provides maximum reliability. The optimal autonomy level is a predefined setting in our model.

5 Discussion

We have developed the concept presented in this paper using a top down approach and performed initial experiments using a simulation. Initially, our focus lies on the definition of a conceptual framework and the identification of the essential elements. State of the art artificial intelligence techniques ranging from classification/regression, self-diagnosis using artificial immune systems, and human-factor research will required for a final realisation of this concept, and be part of our future work.

The illustrated concept uses reliability to represent trust. Since error variance can be of significant importance, e.g. many but small errors compared to few but critical errors, an extension of our trust computation has therefore to be part of further adaptations of the presented concept along with the development of a good confidence computation.

Our concept is based on an intuitive approach in order to formalize the relationship between human and machine. However, applying an optimisation process is required, given that the application of autonomous systems suffers from over- and undertrust into each system. Team efficiency will benefit from a strategy to tackle the issue of over- and undertrust. In Section 4 we gave an example for such an optimisation strategy. Our concept is not limited to mixed teams, but can also be applied to teams of robots only, e.g. for self-organisation purposes in order to reach an optimal usage of the autonomy capabilities of its individual members.

The definition of the autonomy level should reflect the dependency of a system regarding human intervention and the number and importance of required human interactions allows a comparison between autonomy levels. With a higher autonomy level, the frequency of the requests for human interaction decreases, but the importance of an operator's interaction rises. Meanwhile, the self-confidence value has to provide a consistent and reasonable interpretation of the robot's state. A severe risk or challenge has to be reflected in the self-confidence value, while the autonomy level eventually defines whether the robot can deal with the situation itself or not.

6 Conclusion and Future Works

The following sections will provide a brief summary of this paper and an outlook to our future work.

6.1 Conclusions

This paper illustrates the intermediate results of a top down approach of developing a measure for sliding autonomy as part of the project RIMRES. The existing spectrum of autonomy levels and approaches towards realising a sliding autonomy is broad, as we showed in our state of the art collection. However, we described our motivational factors of using a formalised trust based relationship between operator and system and presented a novel approach for a system-initiated switch. It uses operator trust and self-confidence of a robotic system to initiate a switch between three different autonomy modes: manual mode, mixed initiative mode, and full autonomous mode. While we left the details to producing the self-confidence on a conceptual level, our simulation experiments illustrated elements and aspects of the concept. Eventually, this concept is a promising step towards optimising the efficiency of mixed team operations by maximising autonomy and keeping associated risks low.

6.2 Future Works

The current presentation is based on simulated user and system experience. In our future work we will: (a) realise the computation of a self-confidence measure for individual robots, (b) evaluate it by comparing human judgement of a situation versus the system's judgement, (c) extend our concept to address some of the existing shortcomings and (d) embed the self-confidence measure and test the concept presented in this paper on real robots.

7 ACKNOWLEDGMENTS

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