

CoCoRo - The Self-aware Underwater Swarm

Thomas Schmickl, Ronald Thenius, Christoph Möslinger,
Jon Timmis, Andy Tyrrell, Mark Read, James Hilder, Jose Halloy, Cesare Stefanini,
Luigi Manfredi, Alexandre Campo, Tobias Dipper, Donny Sutantyo, Serge Kernbach

Abstract— The EU-funded project CoCoRo studies a heterogeneous swarm of AUVs used for monitoring and search purposes. CoCoRo is planned to be an underwater swarm system that mixes bio-inspired motion principles with biology-derived collective cognition mechanisms in a blended manner. This way a novel robotic system will be designed that will be scalable, reliable and (in parallel) flexible concerning its behavioural potential. We will use self-awareness on swarm-level, which is an emergent result of bio-inspired mechanisms derived from fish, honeybees, immune-systems and neurons. Information will be processed at low levels on a local basis generating collective-level memory and cognition. Another novel aspect will be a bio-inspired operating system that – as default behaviour – allows the swarm to shoal and to maintain coherence. Collective discrimination of environmental properties will be processed on an individual or on a collective level given the cognitive capabilities of the AUVs. Collective self-recognition will be experimented by bio-inspired experiments allowing the quantification of collective cognition.

I. MOTIVATION, BACKGROUND AND INTRODUCTION

A. Why underwater?

The ocean is still the most unexplored habitat on earth. It holds abundant numbers of unknown organisms, it holds undiscovered resources and it holds a magnitude of processes that are not finally understood. In short, ocean exploration is one of the most prominent ‘hot topics’ in science today.

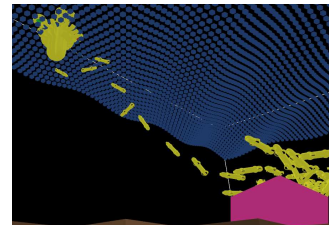
In CoCoRo, we suggest a swarm-based robotic system that allows to efficiently and autonomously search areas of the ocean for specific, hard to find targets. Such targets could be black boxes of sunken planes, valuable resources or toxic waste dumps. The challenge of finding such targets is that they are often hard to locate from the water surface and thus require extensive scouting of the sea bed. Toxic waste, for example in the form of leaking barrels on the sea bed, could produce a very weak and irregular toxin gradient that is very hard to follow for a single autonomous underwater vehicle

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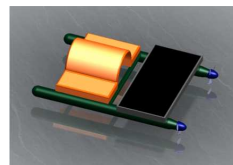
T. Schmickl, R. Thenius and Ch. Möslinger are with the Artificial Life Lab, Department for Zoology, University of Graz, Universitätsplatz 2, A-8010 Graz, Austria {thomas.schmickl, ronald.thenius, christoph.moeslinger}@uni-graz.at

J. Timmis, A. Tyrell, M. Read and J. Hilder are with the Department of Electronics, University of York, UK. {jt517, amt, mnr101, jah128}@ohm.york.ac.uk

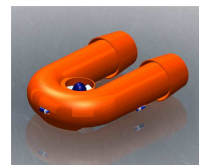
T. Dipper, D. Sutantyo and S. Kernbach are with the Institute of Parallel and Distributed Systems, University of Stuttgart, Universitätsstr. 38, D-70569 Stuttgart {tobias.dipper, donny.sutantyo, serge.kernbach}@ipvs.uni-stuttgart.de



(a) Swarm searching the seabed



(b) Basestation



(c) AUV

Fig. 1. Figure 1(a) depicts the CoCoRo system, comprising the base station on the water surface, a relay-swarm that communicates information to this base station and a ground-swarm that searches the sea bed for a specific target. Figure 1(b) shows the CoCoRo ‘base station’ design. It has many sensors on-board such as GPS communication, sonar, compass, anemometer, inertial sensors. It is able to recharge the AUVs platform. Figure 1(c) shows the CoCoRo ‘AUV’ design. The platform is able to swim in 3D, to achieve zero-power diving, to perform obstacle avoidance. The AUV speed is up to one body length per second. It has on-board many sensors such as distance, pressure, compass and inertial sensor.

(AUV, see Fig. 1(c)) in order to find the source. However, whereas a single AUV would need to utilize a complex and time-consuming search pattern to detect such a gradient, a swarm of AUVs could act as a distributed sensor network (see Fig. 1(a)) and quickly comb through the area. The swarm then could follow such a weak and irregular toxin gradient, find the source and send its location to the base station (see Fig. 1(b)) which could use GPS coordinates to mark the place for the cleanup team.

We think that swarm systems require a 3-dimensional environment (underwater or air) to unfold their full potential. This is due to the scaling issues with increasing swarm size. On the one hand, swarm systems tend to increase their efficiency with increasing swarm size as the number of agent-to-agent interactions increases with swarm density (size). On the other hand, higher swarm densities lead to an increase of blocking (traffic jams) of the moving agents. In 3D environments the number of interactions between agents that can locally communicate is higher, as each agent can have more neighbours around. Thus, the collective computation can be more intense than in a 2D environment. On the other hand,

traffic jamming is not so frequent in 3D, as there are more possible directions that an agent can escape from a jammed position. Thus, we suppose, that swarm intelligence and swarm robotics can show collective cognition and collective intelligence more prominently in a 3D environment than in a 2D world (like epuck robots in a planar arena). The fact that motion in water is usually slow and that buoyancy combined with thruster-driven propulsion offers interesting steering and motion capabilities, will allow this underwater swarm system to exhibit high levels of ‘swarm intelligence’.

B. Why swarms?

A ‘swarm’ is a system of loosely coupled units that interact and interfere with each other by (mostly) simple mechanisms. However, although these interactions can be described by simple rules, the system as a whole is able to exhibit complex behaviours. A coherent group of AUVs may coordinate their motion and collectively process their motion. This has several advantages which are usually attributed by the term ‘swarm intelligence’ [19], [7], [11], its physical manifestation in autonomous robots is usually referred to as ‘swarm robotics’ [5], [6]. Such robotic systems exploit the principles of self-organization in a similar way as their natural counterparts do, allowing collective decision making and group-level homeostasis [8].

Often such systems are scalable, thus adding swarm members does not impair the efficient functionality of the collective system. Such systems are also often flexible, as swarms are not easily trapped in local optima and they are able to exhibit many variants of collective behaviour. In addition, they tend to be robust: it does not matter if some swarm members get lost, the system can still achieve (some of) its tasks. Most prominently, it is a characteristic of such systems that the collective system is able to solve problems that each individual cannot solve alone.

C. Why self-awareness?

In real-world underwater environments, sensors of AUVs are much more subject to noise than land robots’ sensors, even under typical laboratory conditions. Imprecise sensor information, coupled with the constraint of not being able to communicate over large distances narrows down the capabilities of single AUVs. Using swarms of AUVs is our way to extend the capabilities of AUVs. However, being an autonomous member of a swarm requires special abilities from an AUV, namely it has to be aware of its own state and the state of its swarm. It should, for example, know which swarm it belongs to (ground swarm vs. relay swarm), it should know the size of its swarm and it should also know the status of the swarm (target status, energy status, etc.). After combining these information with the knowledge of its own status (e.g. depth, battery status, etc.) each single AUV should then make the right decision that contributes the most to the swarm’s efficiency. This kind of generated self-awareness of each swarm member is a key aspect of the CoCoRo project and should help the swarm to meet the following challenges.

II. CHALLENGES, TASKS AND EXPERIMENTS

A. Which tasks does the swarm have to solve?

1) *Deploy the swarm to the water:* Due to their very small size the CoCoRo AUVs can be deployed by hand from a boat or from the shore. At first the base station is deployed in the mission area, then the AUVs have to stay near this base station without losing contact with it.

2) *Search for a target on the seabed:* The CoCoRo AUVs should search the seabed for a specific target. Finding such a target will only be efficient if the AUVs work together.

3) *Discriminate between multiple targets:* If multiple targets are found by the same group of AUVs, the AUVs have to be able to discriminate between these targets.

4) *Select the best of these targets:* If several targets are detected, AUVs have to evaluate criteria that allow to discriminate between targets of different quality. The swarm has to be able to select the target of highest quality.

5) *Communicate search success to the water surface:* After the swarm has located a target on the seabed the swarm should report the target’s position and quality to the base station.

B. Which challenges do these tasks pose for the swarm?

1) *Do not get lost in the ocean:* AUVs can easily get lost in the vast ocean. To prevent this the base station will create a ‘virtual fence’ by emitting an acoustic signal that indicates the distance to the base station. This is used to let the AUVs know when they are too far away from the base station and when they should turn back. The AUVs should also be able to automatically get back to the surface in case of malfunction or low batteries.

2) *Join multiple AUVs to one functional unit:* A group of AUVs that is responsible for a given function within the swarm has to build a sub-swarm. The coherence of this sub-swarm is based on local communication channels.

3) *Utilize group-level interaction to increase performance:* Within a swarm, different autonomous groups of AUVs (sub-swarms) have to interact in a coordinated manner. These interactions on the group-level can be based on local and on global communication channels.

4) *Cope with a noisy and heterogeneous environment:* On all levels (swarm level, group level, individual level) the AUVs have to deal with problems like sensor noise, changes in buoyancy due to external changes (e.g. water temperature or salinity), delocation of individuals by underwater currents, and interaction with marine flora and fauna (fields of seaweed, small fish schools near objects on the seabed). These sensor noise can be compensated by using the AUV swarm as a distributed sensor network.

5) *Compensate unavoidable losses of swarm members:* If an AUV gets lost due to unforeseeable events, the swarm has to detect and to compensate for this. The AUVs will be able to continue their tasks on all levels, with only a small decrease in efficiency, due to the self-organised nature of the used swarm algorithms.

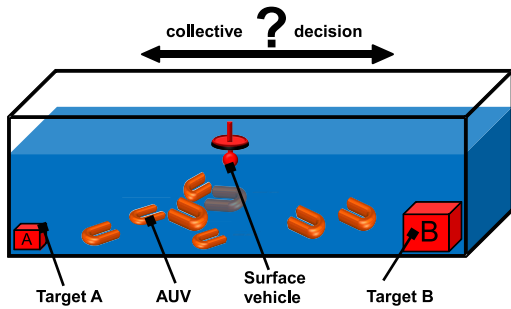


Fig. 2. Collective discrimination between two environmental choices by a CoCoRo swarm system.

C. How can experiments benchmark swarms in these tasks?

We have devised a generic experimental setup which will allow us to benchmark the CoCoRo system in the tasks aforementioned. The setup will consist of a water tank approximately 3 m deep and of at least 10 m² of surface. The bottom of the pool will be covered with seabed-like patterns for more realism. This way robots may use optical flow to estimate their displacement and roughly localize themselves. We will use specific objects for detection by the AUVs. These objects should be seen as a metaphor for toxic waste or flight data recorder that must be located in the ocean. First, these objects will be actively emitting signals detectable by AUVs. Later on, we will also experiment with passive objects which may only be distinguished by their colour.

With this experimental setup, we will be able to use a CoCoRo system composed of one surface station and a swarm of AUVs. We plan to make experiments of incremental difficulty, because the tasks of the robots are related and interdependent: In a first experimental series we will drop a single target on the tank's bottom. The AUVs will shoal and explore the tank to locate the target, simultaneously maintaining a connected topology to avoid losing any AUV and maintaining a physical chain to stay in touch with the base station. A second series of experiments (see Fig. 2) builds upon the first one. We will introduce a target object together with distractor objects that resemble the target. The system will have to discriminate between these objects and process information from multiple noisy measurements to select the target object. These experiments will provide quantitative results on the performance of the swarm in various tasks. Indicators and statistics of interest will notably include the ability of the system to maintain its operational state, the robustness to failure or loss of AUVs, as well as speed and precision of the system.

III. BEHAVIOURAL CONTROL AND ALGORITHMS CREATE AWARENESS

A. How can awareness be used on the individual level?

Today's AUVs are strongly limited in performance and abilities by the fact that they operate with pre-programmed tasks that specify platform parameters during the entire missions. To overcome these limitations it becomes necessary to

produce a robotic system able to take autonomous decisions in order to react to unforeseen and changing events. This kind of situational awareness, that can be reached thanks to a dense net of sensors, actuators and data processing properly coordinated by the algorithms of the control system, is the core for developing vehicles that are able to recognize themselves and take decision autonomously. At individual level this fusion of sensors, actuators and data processing will allow to have modules able to manage internal malfunctions and, at the same time, unpredictable events. In fact, in tasks that require long time to be achieved, the ability to self-determine the capacity to carry these tasks out (in terms of autonomy, failures, ability and environmental conditions) is of vital importance, not only for reaching objectives but also for the safety of the system. This suggests that a conservative approach is fundamental for handling critical errors or abnormal events: in such situations an emergency ascent will guarantee the survivability of the robot.

B. How can awareness be used on the group level?

One of the 'big vision' scenarios for CoCoRo is the search for toxic dumping places on the seabed. Such places are generally hard to find for single AUVs which are rather inefficient at combing through suspected dumping areas. A swarm of AUVs, on the other hand, can quickly and efficiently comb through such areas. However, just combing through the area and logging the position and local toxin levels is not the goal of our swarm. Instead, we will program our AUVs to use group-level awareness to *locate* the actual dumping place. This will be done by letting the AUVs interact in a certain way that will generate an emergent taxis behaviour where the swarm as a whole will move uphill the toxin gradient until the source is found. This emergent taxis behaviour is a swarm behaviour that usually increases in efficiency with swarm size. Preliminary simulations have shown that such a behaviour is even possible without explicit communication between the AUVs.

Another aspect of work in CoCoRo will be the exploitation of group level awareness to initialise and achieve self-repair. Our work will take inspiration from immunology in providing algorithms capable of detecting errors in individual AUVs, and at the group level within a swarm, and then afford a recovery mechanism from such errors. This recovery mechanism will allow the swarm to re-organise in such a manner as to allow the swarm to maintain operation despite the occurrence of faults. As our inspiration for this, we will exploit a self-recovering mechanism observed in the immune system. The murine autoimmune disease experimental autoimmune encephalomyelitis (EAE) is a model for multiple sclerosis in humans. Many mice induced into EAE spontaneously recover from autoimmunity [16]. This is mediated through a regulatory network of cells that recognise, monitor and respond to the actions of autoimmune T cells. By adopting algorithmic principles from the manner in which these mice are able to recover from autoimmunity, CoCoRo AUVs will monitor one another, detect behaviours of individual swarm members which are detrimental to the overall performance

or goal of the swarm, and react accordingly. Such corrective responses may be limited to individual AUVs, or may spread across several robots to constitute a collective response. To illustrate, the failure of an individual robot in a chain-like group which relays information between two locations may be perceived by several other individuals that recognise a loss in quality of this group's performance. Each of them may generate an appropriate response maybe even affect its neighbours: As a collective, some robots alter their behaviour to restore the swarm's quality of service.

C. Generating and using awareness on the swarm level

On the swarm level, self-awareness allows the swarm as a whole to monitor and to regulate its own collective activity. Mechanisms for creating (self-)awareness may be distributed over several groups, depending on the capabilities of agents to perform computation, communication, or more generally, to maintain the required level of interactions.

In CoCoRo we will use following approaches for creating awareness at the swarm level. One method is 'self-adapting Artificial Neural Networks' (ANNs), which are modulated by global or local information spread throughout the self-organised AUV swarm. These modulations can be interpreted as 'moods' or 'emotions'. The messages that are spread throughout the swarm can be quite simple compared to the communication required to coordinate a group of agents conventionally. In CoCoRo, a single AUV (or a group of AUVs) can modulate behaviours of other AUVs by spreading messages via local or global information channels. The modulation of these individual behaviours will lead to a change of behaviour of the whole swarm due to the self-organised nature of the AUV "superorganism". The advantage of this approach is to re-use neural structures that are necessary in all modes of operation, while only those parts of the ANN are modulated that are relevant for the given task. Such systems allow to interweave nodes which are modulated with nodes that are not modulated. This way the awareness about the current situation of the swarm is coded in the distribution of behaviour-modulating messages within the swarm. Due to an unequal distribution of information (e.g., due to usage of local communication channels) members of the swarm behave differently in different parts of the swarm, which results in a division of labour. Examples of such modulatable ANNs are found in [23]. See [10] for an overview of artificial emotions and swarms and see [9], [2] for an overview of modelling emotions and neuro-modulation.

Another closely related approach is based on nonlinear oscillators coupled by means of an electrostatic field [14]. This is efficient for small underwater vehicles due to a small required computational effort able to generate multiple collective phenomena [12], e.g., in collective decision making [15]. The water is a shared communication medium, thus this approach can naturally involve globally coupled systems (e.g. mean field) [3]. Achieving self-awareness in such systems can be based on well-known dynamical systems such as travelling waves in spatially excitable media (e.g., FitzHugh-Nagumo systems [24]), on the introduction of

delayed feedbacks [18] or on other methods to reflect the global status locally. Such dynamical processes represent collective models that can handle distributed sensor data and perform reasoning about common activities [13].

Although single swarm members may not have access to information at the global level (i.e. information about the group's activity) the swarm itself can process such information in a decentralized manner in order to regulate and adjust its common activities. We consider, for instance, a task of collective discrimination: The system is confronted with two or more objects and has to identify and select a target object. Single AUVs have limited sensory capabilities, thus they are not able to monitor the activity of the group in its entirety.

One first problem that would be alleviated from swarm-level self-awareness is the detection of task completion. The swarm must know whether it has completed its task in order to transmit information about its findings to the base station, or simply to switch to a new task. This metacognitive information may be obtained by implementing a mechanism of quorum sensing to have the AUVs gather information and collectively agree on when their objective is attained.

A second problem arises when the objects detected by the swarm are rather similar. Discrimination is more difficult to accomplish in that case, and the swarm is more likely to make errors, and in the worst case to choose randomly between the alternatives because they are too hard to distinguish. If the swarm realizes the difficulty of the task, it can report about its uncertainty rather than making a mistake. For instance, if the opinion of the AUVs oscillates between several alternatives without stabilizing, the swarm may trigger a specific response indicating uncertainty, which would in turn improve the correctness of its decisions.

IV. FOUNDATIONS OF AWARENESS: HARDWARE, ELECTRONICS AND OPERATING SYSTEM

A. Which hardware constraints do exist?

The design of an AUV platform needs to take into account different aspects since vehicles have to be truly autonomous and, in the meantime, have to operate in an underwater environment. Concerning the size of the platform, a small robot would be the ideal solution for improving the system dynamics (less inertia) and performing tasks in extreme environments. However, size is strictly related to the onboard volume necessary to allocate batteries, electronics and mechanical systems. It is therefore necessary to find a good compromise between size, technology constrains and autonomy. The latter plays a fundamental role in underwater robots and depends on many factors such as shape, hardware requirements, processing and sensing. In fact, hardware and software complexity affects the required power, in turn changing significantly the efficiency of the system. For this reason it becomes vital to find ad-hoc solutions for developing hardware systems with high efficiency and to avoid sensing and processing redundancy.

For exchanging data wireless communication will support swarm control and self-awareness. From this point of view

there are many aspects that must be taken into account in the designing such as: bandwidth, range, power and communication protocol. It is also important to consider that wireless communication in underwater environments is not efficient, thus new kinds of communication are to be considered. Finally, the embedded CPU and operative system needs to be defined as a compromise between boards, size, computational burden and power consumption. This choice is fundamental for ensuring the feasibility of required computations (data processing) and for ensuring AUV's autonomy.

B. Hardware design maximizes awareness on all three levels

High-level behavioural algorithms need information about AUVs to plan and actuate control strategies. These data have to be shared between modules and for this purpose wireless communication plays a fundamental role. Since the amount of data that have to be exchanged is high, in order to maintain the minimum bandwidth necessary for communication, an efficient communication protocol has to be implemented. Having a swarm of small AUVs distributed over a wide area allows that some tasks can be performed more accurately and quickly than with one bigger vehicle. In fact, onboard sensors allow to achieve global vision of the environment and to plan autonomous swarm control strategies. Sensors for interacting with the environment must be defined based on each task the swarm – and in turn also each robot – has to accomplish. For instance in flocking, it is essential to sense the intensity and the direction of water currents in order to plan the trajectory of the entire swarm and avoid collisions. Onboard sensors (e.g. battery energy check, inertial and distance sensors) are dedicated to support the behavioural algorithms of single AUVs, giving them the capability to plan their work autonomously.

C. Sensors & communication support high-level behaviours

Local sensing allows distance measurements, colour detection, detection of the spatial position of a signal, robot-object and object-object discrimination, and recognition of object shapes. It also includes other sensing systems such as 3D accelerometer, compass, pressure sensor, humidity/temperature sensors, energy sensors. Distance measurement can be based on absorption properties of water (for example 1dB/m for optic, 40 dB/m for RF100MHz and 100dB/m for electric field), which depends on frequency/wave-length, salt concentration, pressure and several other parameters.

When the distance measurement system is calibrated in the test conditions, attenuation of the signal provides information about the distance between sender and receiver. Due to a lower absorption, optical system is the most suitable for this purpose. Maximal distance can be calculated from the condition that an analog blue light LED at 40-60mW and 10 degree opening angle can be sensed by a photodiode (with amplifier) at the distance of 1.2-1.4m. Provided the surface reflect 80% of a signal, the sensing range (based on reflection) is about 0.4-0.5m. Thus, active distance measurement, when an object is equipped with an emitting LED, is more preferable, since this allows a larger sensing radius R_s . Sensing range can

be improved by emitting more light energy, however this does not always effectively increase the sensing radius. For instance the approach discussed in [22] leads only to 2.1m direct sensing for 400mW cyan LED.

Another approach for distance measurement can be based on the flying time (between sending a signal and receiving its reflection), so-called active acoustics. The relatively low sound travel speed of roughly 1500 m/s (this requires measurement of time in μs scales, which can be easily implemented by e.g. phase-detection approach) makes hydro-acoustic waves well suitable for these purposes. Hydro-acoustic approach is well researched, however it requires computation-intensive noise-cancelling and reconstruction techniques, especially in case of hydro-acoustic arrays [4].

Optical systems with integrated optics allow focusing the light and so increase the sensitivity. There are several works which describe application of cameras for underwater navigation [20], however also point out a complexity of image processing tasks [21]. For the development of a small platform, the optic distance measurement system is more preferable due to simpler electronics and unsophisticated signal processing. To provide directional sensing, the platform can be equipped with multi-channel systems. Application of an active acoustic approach can be investigated when a long range of sensing distances is required.

Local directional communication can be established by analog and modulated light; omni-directional by electric field and low-frequency RF (frequency or emitting power affect the communication radius R_c). The communication distance and bandwidth are co-dependent values, increasing one of them decreases the other one. The best tested transfer rate for a local optical communication is 119 kbps with IrDA QAM modulation. Acoustic and ultra-low-frequency RF can provide global omni-directional communication (max. range of hundreds of meters). Sonic waves travel very well under water and the energy and build-space required for generating and receiving them is relatively low. This approach is used in acoustic modems [1]. Drawbacks of this approach are multiple reflections causing distortions in the signal. Therefore, acoustic signals can be used as a global communication system for very short analog signals.

RF systems represent a trade-off between the frequency (i.e. communication distances) and the size of integrated antennas (i.e. the size of platform). Due to water connectivity, the attenuation of radio waves depends on the used frequency, which in turn results in the size of antenna. High frequencies (> 100 MHz) only need a small antenna (0.1 m) while their range is restricted to 2.5 m. Lower frequencies (100 kHz) have a long range (100 m), but need a large antenna (100 m). Communication ranges of standard 900 Mhz (GPS) and 2.4 GHz (ZigBee) are only of 10 cm and 2.5 cm correspondingly. For such systems, the control circuits are more complex than those for optic or acoustic approaches. Since bandwidth for low-frequency RF is not sufficient for application of standard protocols (e.g. ZigBee), global RF communication has still some open problems. Depending on requirements for global communication, both, acoustic and

low-frequency RF S&C can be implemented (acoustic one is more favourable due to less complex hardware).

D. Operating system supports awareness of the system

The self-aware properties of swarms that CoCoRo seeks to investigate all emerge from the perceptions and behaviours of individual members of the swarm. Successful operation of these algorithms requires that individual swarm members can perceive and compute in real-time. CoCoRo will investigate the role of light-weight artificial immune system algorithms, which have a proven track record in anomaly detection problems, in fault detection in individual swarm members. For example, these algorithms can be used to predict and manage processor schedule overruns [17]. We will also embed a default behaviour in the operating system: all robots that are running the operating system will boot up into a state such that their default behaviour is to school.

V. CONCLUSIONS

In this article we argue for cognition and self-awareness as a crucial prerequisite for a functioning swarm of underwater vehicles. Cognition on all levels (individual, group & swarm) is necessary because such swarms have to act autonomously, environment is harsh and sensor data is very limited. The key issue is to design AUVs in a way that collective cognition-generating mechanisms can work efficiently and that the most individually collected data is exploited by the system. We discussed in detail the constraints on AUV design as well as limitations and possible workarounds in underwater communication and sensing. Without a certain level of cognitive capabilities a collective system of AUVs will not be able to stay together and to 'understand' the environment. Self-awareness, self-monitoring and self-control are important to prevent malfunctioning of the robotic system in harsh underwater environments. We have chosen to go for a swarm system in CoCoRo, as these systems are usually robust, scalable, flexible and operating with limited actuation and sensing capabilities. However, the swarm approach forces us to make each individual AUV small and cheap, in turn limiting sensor and actuation potential. At the end, we will have to find a good compromise between size and costs on the one hand and equipment and capabilities on the other hand. Self-awareness and cognition is nothing that can be simply measured. Instead, the domains of ethology and psychology have developed a set of experimental setups to measure cognitive functionality in living organisms, because brains are more or less a black-box for the experimenter. We took over these approaches and will measure the collective capabilities of our robotic system with similar experimentation. This might surprise the engineering community but is well reasoned by the fact that we will strongly exploit bio-inspiration and self-organization to generate collective cognition in our system. Thus, cognition and self-awareness will be emergent phenomena, thus they will be black-boxes to us. By investigating such distributed cognition systems, not only a set of engineering problems will be solved but also basic research in cognitive science will be performed.

VI. ACKNOWLEDGMENTS

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