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Towards Mixed Societies of Chickens and Robots

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***Abstract*— To design, to study, and to control mixed animals-robots societies is a challenging field of scientific exploration that can bring new frameworks to study individual and collective behaviors in animal and mixed robot-animal societies. In the Chicken Robot project we aim at developing a mobile robot, able to collaborate with a group of chicks and to control certain group behaviors. The first research step is to build formal models of relevant animal behaviors by performing ethological experiments. Hence, one of the principal tasks is to design a setup equipped with appropriate monitoring tools. In this paper, we present a toolset for running chick-robot experiments and analyzing results. It includes an autonomous PoulBot robot and an experimental setup, able to autonomously record experimental video and audio data, to detect displacements of chicks and robots, to detect their calling activity and to provide robots with these data. We also present a visual data analysis system to extract behavioral features of individual chicks using the variational Bayesian Gaussian mixture model classification with a particle filters based prediction of future positions of chicks. We show how these tools are currently used to carry out chick-robot experiments, to collect behavioral data and to extract animal behavioral features that allow us to build behavioral models bound to be implemented in the robot.**

I. INTRODUCTION

In ethological studies one of the long-standing interests is to understand social communication, relationships and structures. Until recently to study these mechanisms researchers had used specially designed simple mock-ups whose behavior can be controlled in details to monitor a response of the animals. But nowadays availability of low-cost miniaturized computer chips, motors and sensors allowed these artificial models to become sophisticated robotic devices that can be used to test hypotheses, which were too tricky to work with before [1]. For instance, robots were used to study male territorial instinct in dart-poison frogs [2] and mate selection in tungara frogs [3], to test ideas about nest mate recognition in brush turkeys [4] and the predator avoidance by ground squirrels [5]. However, most of these robots still had a small number of sensors, a limited computational power and very little or no autonomy; they were able to test only one or very few specific behaviors.

We, on the contrary, aim to develop a mobile robot, equipped with a wide range of sensors (video cameras, microphones, proximity sensors, etc.) and a sufficient computational power, which will allow ethologists to study more sophisticated phenomena. The scientific questions that will be addressed using this kind of robotic system are the link between individual and collective behavior, the role of inter-individual variability in collective decision making and the cognitive capabilities required, such as sound communication, color perception and pattern recognition. From a biological point of view we chose the domestic chicken (*Gallus gallus domesticus*) as a model animal; the domestic chicken is a well studied animal model that gives us a solid knowledge base; it is also one of the most important farming animals and we believe that our results could be translated in the poultry industry to improve chicken welfare and breeding conditions. The robot has to be able to interact with animals by using relevant natural communication channels, to send cues to the animals, to perceive their responses and to respond to them. Thus, the system has to close the loop between the animals and the robots, i.e. they both have to exert a mutual influence through a lasting relationship. In this case, at the individual level, the robot has to be capable of perceiving the animal location through vision or by other sensors, to perceive sound signals emitted by the animals, to detect zone of interest either according to their luminosity or temperature. These perception capabilities have to be put into a relevant behavioral context by the robot, i.e. not only does the robot need to be capable of perceiving a certain cue but it needs also to be able to understand its meaning related to a context, and to send a relevant visual or sound response. This implies that we will need to develop cognitive models for the robot. These cognitive capabilities will also be used to assess its role and impact at the collective level.

Methodologically our project continues the European project Leurre, where mobile microrobots were designed to study and control the social aggregation in cockroaches [6]. Other projects that address related questions are the research on smart collars aiming to study and potentially control the herding behavior of cattle by building a virtual fencing system based on the interactions between the animals and the network of collars [7], [8], and a Robot Sheepdog Project, where a mobile robot was designed to shepherd a flock of ducks and to lead them safely to a specified position [9]. In [10], [11] the researchers designed the WM6 rat-like robot to teach a rat to push a lever to access a food source, and an autonomous experimental setup for real-time measurement of rats behavioral parameters. The main difference from our previous project is that we work with animals that have different cognitive and communication capabilities than cockroaches, i.e., here we mainly use learning (imprinting),

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sound and vision instead of tactile and olfactory communication. Compared to most of other projects on animal-robot interactions, we deal with group of animals interacting with each other and with autonomous robots instead of one-to-one interactions; we also aim at integrating the robot into the animal society building upon social behaviors.

In this paper we present our current progress in the project. We developed a robot for chicken-robot experiments and implemented a behavior based control system; besides this, we built an experimental environment equipped with recording and remote monitoring system, and designed a toolset for analysis of recorded experimental video data, where variational Gaussian mixture models and particle filters are used to extract relevant behavioral features. We show how these tools are currently used at Université Libre de Bruxelles (ULB) in studies related to the decision-making mechanisms in chick groups, the role of leadership in group behavior and the impact of inter-individuals differences on collective behaviors.

The paper is organized as follows. Section II gives a brief overview of the experimental setup. Section III describes a PoulBot robot, its vision and control systems. Section IV presents a remote monitoring interface. Section V describes a system for semi-autonomous extraction of individual behavioral features from the recorded video, followed by experimental results in Section VI.

II. OVERVIEW OF THE EXPERIMENTAL SETUP

The experimental setup is composed of the following components:

- an experimental arena;
- an overhead camera;
- a standalone experimental PC.

For experiments on the audio communication the setup can be additionally equipped with a specially designed microphone array [12].

The experimental arena is a flat square 3 by 3 meters surrounded by a wooden wall of 60 cm height (Fig. 1). The floor is painted in black to simplify the tracking task. The lighting has the reduced infrared (IR) emission to decrease a noise on the IR proximity sensors of the robot. The experimental PC runs the vision system, the Graphics User Interface part of the robot control system, and records experimental video data and audio data, in case if the microphone array is used. The input video data is processed by a real-time vision system that detects chicks and robots. When the microphone array is used, the PC can also run a real-time sound calls localization system, based on the frequency domain beamformer [12]; its output is probabilistically mixed with the vision system output to detect calling chicks.

III. POULBOT – A MOBILE ROBOT FOR ANIMAL EXPERIMENTS

A. Design of the Robot

The design of an appropriate body and behaviors of the robot for animal experiments must originate from relevant sensory modalities and behaviors of the animal under study.

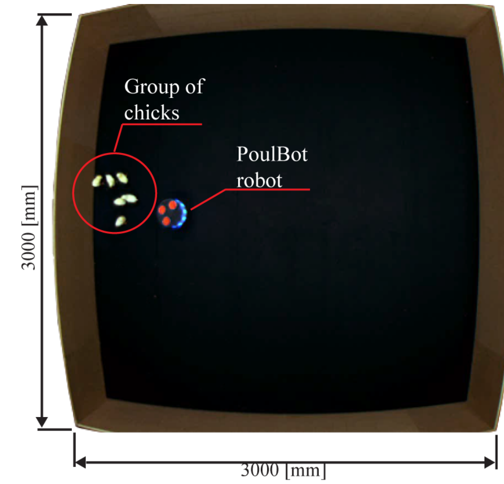
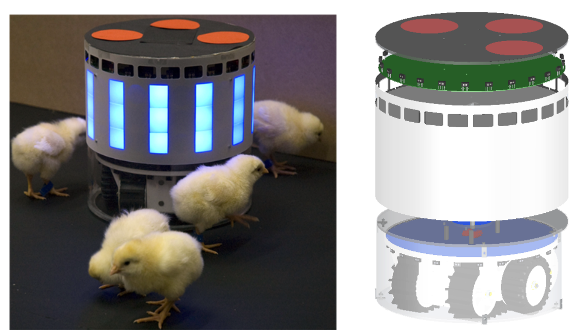


Fig. 1: The experimental arena with the PoulBot robot and a group of chicks

We do not copy the animal in all its aspects, instead we focus on the relevant constraints. It is not always necessary for a robot to look like an animal under study; for example in the Leurre project the InsBot robots resembled the cockroaches only in size, but they were accepted by the animal group thanks to the special pheromone spread on the robots [6]. When working with domestic chickens we can also profit from the natural learning mechanism called filial imprinting [13]; if shortly after hatching we present the moving and vocalizing robot to chicks they learn that the robot is the mother. Afterwards chicks are attracted by the robot and demonstrate a following behavior. Because variations in size, shape and color are well tolerated for imprinting, it is not necessary for the robot to look like a hen.



(a) The robot with an activated sample color pattern

(b) The design of the robot

Fig. 2: The PoulBot robot and its design. The modules are, from base to top: a base, a plexiglas bumper, a color pattern module, an extra IR sensors ring and a top markers board

The PoulBot robot (Fig. 2) that we use in experiments is a track-type mobile robot that has a size of an adult chicken. The robot is a modification of the marXbot mobile robot [14]; the marXbot is a modular robot that consists of a locomotion base and various application specific modules, fixed on it. Among other sensors, the base provides 24 infrared proximity sensors around the robot, a gyroscope, an accelerometer and contains a replaceable 38 Wh lithium polymer battery. We extended the base by adding a plexiglas bumper, a color pattern module, an extra IR bumper, a speaker, a top markers board, and Bluetooth connectivity.

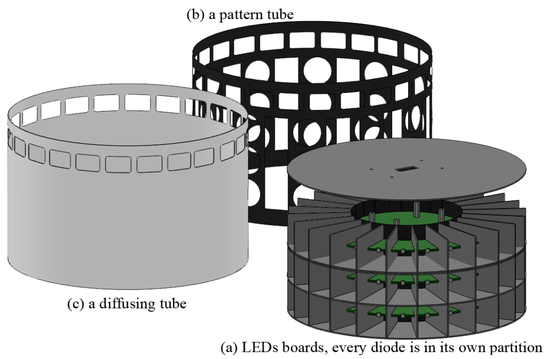


Fig. 3: The design of the color pattern module

The color pattern module serves to improve and control the efficiency of filial imprinting and to study cognition in chickens. Its design is based on three rings of RGB LEDs mounted one above another, a diffusing plastic tube and a nontransparent replaceable pattern tube (Fig. 3). Every LEDs ring consists of 24 diodes that are driven by a dsPIC33 microcontroller and separated from one another by nontransparent horizontal and vertical partitions to reduce the light diffraction. Intensity and color of every LED can be set separately, thus allowing to produce a variety of color and spatial combinations; thanks to the replaceable pattern tube different shapes of pattern elements can be tested. The additional IR sensors ring is placed above a chick height and is used in combination with IR sensors of the base in case when we want the robot to behave differently if it detects a wall or a chick. The plexiglass bumper protects chicks from being caught by accident by the robot tracks. Markers on the top of the robot are used by an external vision system, described below to detect the position and orientation of the robot.

B. Vision System

To track robot and chick displacements we use the color Basler scout Gigabit Ethernet camera scA1000-30gc. It takes images of the experimental arena (1032 x 778 pixels) like one on the Fig. 1 with a frame rate 10 fps. The image processing is performed by the SwisTrack software, initially developed for the Leurre project to track cockroaches and robots [15].

The robot position and orientation are defined by three color markers on top of it, they can be detected by subtracting the color of the markers from the input image and binarizing the result with a predefined threshold. Chicks are mostly white-yellow, so they can be detected by using the same procedure. All positions and distances are measured in the real-world coordinates thanks to the calibration routine based on the well known Tsai's calibration technique; for our setup an average absolute calibration error is 3.1 mm. The detected positions of robots and chicks are further transferred to the robot controller, where they are used when a behavior executed by the robot needs them.

C. Behaviors of the PoulBot Robot

The large number of onboard sensors implies that a control system has to be relatively complex; since the main interest and concern of biological researchers lies in a proper setting and in conducting animal experiments and not in operating an intricate control interface, our goal is to hide this complexity and to provide a robust and easy to use control system. The control system of the PoulBot robot consists of two parts: an embedded robot controller and a PC part. The embedded robot controller runs on seven dsPIC33 microcontrollers of the robot, one for each motor, one to manage the sensors of the base, three to control the color pattern and one to manage the top IR board. The event-based data exchange and coordination between the microcontrollers are provided by the ASEBA framework [16]. ASEBA also includes an IDE to program microcontrollers with a MATLAB like scripting language.

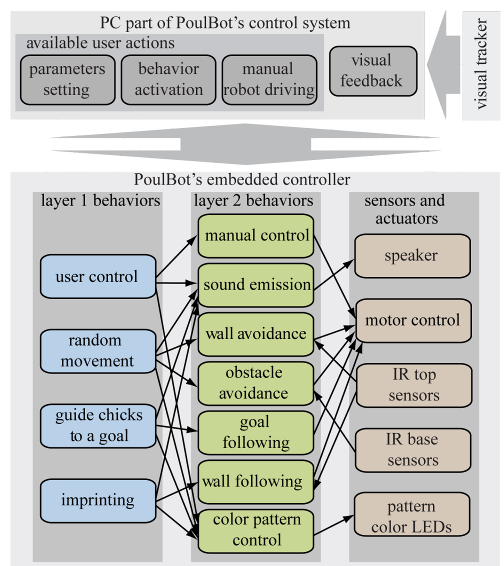


Fig. 4: An overview of the control system of PoulBot

The distributed robot controller is in essence a behavior based controller: PoulBot is equipped with a number of basic behaviors such as obstacle avoidance, wall following, random walking, goal following, calling, etc.; these behaviors can be combined together to form higher level behaviors needed for specific experiments (Fig. 4). Some behaviors use visual information, for example during random walking the robot can check whether the group is following and in case if the chicks are far behind, it can stop and wait them or call or go back, etc. The basic behaviors can be tuned by merely changing their parameters such as motors speed, sensors thresholds, LEDs color and intensity and so on.

The GUI part of the control system runs on the PC; it provides the user with the information on the status of the robot, such as a battery charge level and a current executed behavior, allows to tune the robot behavior parameters and transfers the tracking information from the vision system to the robot embedded control system through the Bluetooth connection.

IV. RECORDING AND MONITORING

Besides tracking robots and chicks, SwisTrack is responsible for video recording of the experiments. Nobody is allowed to be in the experimental room while the experiments are running, to observe a situation on the arena we developed a lightweight and simple remote viewer that connects to SwisTrack through TCP/IP and provides a 3D representation of the arena (Fig. 5). The data stream is coded by using NMEA 0183 protocol; since only coordinates are transferred, the load on the network is considerably lower than if we would transfer the video stream.

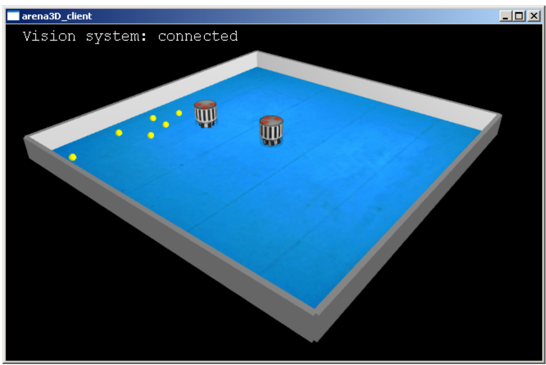


Fig. 5: The remote monitoring interface gives a virtual representation of experiments in the real time

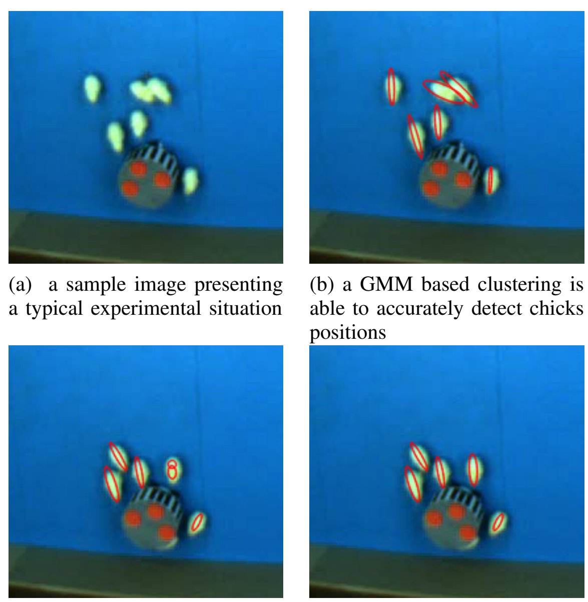
V. EXPERIMENTAL DATA ANALYSIS

A traditional way to analyze experimental data in ethological studies is to manually mark the positions of animals on the video record and to tag their behavior frame by frame at a given timescale. There are several commercially available animal vision tracking and behavior analysis systems that attempt to automatize this procedure. Noldus Information Technologies offers EthoVision [17] video tracking, analysis and visualization system for automatic recording of activity, movement and social interaction of various kinds of animals. To distinguish individual animals it uses color markers. Other solutions are the SMART video tracking system [18] designed for an animal video tracking and analysis of behavioral tests (mazes), the Home Cage Video Tracking System [19] that focuses on locomotor behavior of laboratory animals in their home cages and the Video Tracking System [20]. These software mostly employ simple image processing techniques, e.g. thresholding and background subtraction, often they are tuned to work with rats and mice, are mostly calibrated for animal behavior related to drug testing in pharmaceutical studies, and allow to track only one animal or several animals in separated enclosures. Vicon Motion Systems provides a comprehensive solution to tracks human, animal and other objects automatically [21], but it is hardly affordable for most research laboratories.

In our experiments chicks share the same enclosure as a group. To avoid biased behavior we do not mark them with color markers. That is why to analyze the experimental data we designed our own tracking solution, where we use a variational Bayesian Gaussian mixture model classification with the particle filters based prediction of future positions of chicks.

A. Chick Detection by Variational Bayesian Gaussian Mixture Based Clustering

To build a behavioral model of the chicks we extract individual trajectories from the recorded video data. In this case we rejected to use the simple blob detection to detect chicks because of its low reliability – if two or more chicks are close to one another only one blob will be found. The Gaussian mixture model (GMM) based clustering approach, which is one of the popular techniques for image segmentation, demonstrates good detection results (Fig. 6b), but when the classical maximum likelihood (ML) method is used for training, it suffers from the over-fitting problem in case if some of chicks are accidentally hidden behind the robot (Fig. 6c). On the contrary, the variational Bayesian approach [22] handles this problem by adapting the number of components and pruning the components that are not used. It is also free from the singularities problem of the ML-based training approach.



(a) a sample image presenting a typical experimental situation

(b) a GMM based clustering is able to accurately detect chicks positions

(c) but GMM clustering suffers from the over-fitting when some chicks are not visible

(d) a variational Bayesian GMM adapts the number of component in the mixture

Fig. 6: The detection of chicks positions by variational Bayesian GMM

The points distribution is modeled by the mixture of K Gaussians as follows:

$$p(\mathbf{x}) = \sum_{k=1}^{K} \pi_k \mathcal{N}(\mathbf{x}|\mu_k, \mathbf{\Lambda}_k),$$

where μ_k, $\mathbf{\Lambda}_k$ and π_k are the mean vector, precision matrix and mixing coefficient of the k-th Gaussian. The priors over these parameters are chosen to be a Dirichlet distribution $\mathrm{Dir}(\pi|\alpha_0)$ for mixing coefficients, Gaussian distribution $\mathcal{N}(\mu_k|\mathbf{m}_0, (\beta_0\mathbf{\Lambda}_k)^{-1})$ and Wishart distribution $\mathcal{W}(\mathbf{\Lambda}_k|\mathbf{W}_0, \nu_0)$ for mean and precision of each Gaussian component. The optimization of the variational posterior distribution is carried out by an iterative algorithm that consists in two steps, similar to the E and M steps of the maximum likelihood EM technique:

(E)xpectation step: We compute values r_{nk} representing the posterior probabilities that k-th component is responsible for generating the data point $\mathbf{x}_n$:

$$r_{nk} = \frac{\rho_{nk}}{\sum_{j=1}^{K} \rho_{nj}}.$$

Here

$$\ln \rho_{nk} = \psi(\alpha_k) - \psi\left(\sum_{k=1}^{K} \alpha_k\right) + \frac{1}{2}\sum_{i=1}^{D} \psi\left(\frac{\nu_k + 1 - i}{2}\right) +$$

$$+\frac{D}{2}\ln 2 + \frac{1}{2}\ln|\mathbf{W}_k| - \frac{D}{2}\ln(2\pi) - \frac{D}{2}\beta_k^{-1} -$$

$$-\frac{\nu_k}{2}(\mathbf{x}_n - \mathbf{m}_k)^T \mathbf{W}_k (\mathbf{x}_n - \mathbf{m}_k),$$

where D is the dimensionality of the data variables $\mathbf{x}$, and ψ is the gamma function.

(M)aximization step: We recompute the variational distribution over the parameters:

$$\alpha_k = \alpha_0 + N_k, \quad \beta_k = \beta_0 + N_k, \quad \nu_k = \nu_0 + N_k,$$

$$\mathbf{m}_k = \frac{1}{\beta_k}(\beta_0 \mathbf{m}_0 + N_k \bar{\mathbf{x}}_k),$$

$$\mathbf{W}_k^{-1} = \mathbf{W}_0^{-1} + N_k S_k + \frac{\beta_0 N_k}{\beta_k}(\bar{\mathbf{x}}_k - \mathbf{m}_0)(\bar{\mathbf{x}}_k - \mathbf{m}_0)^T,$$

where statistics $N_k, \bar{\mathbf{x}}_k$ and $\mathbf{S}_k$ are computed as follows

$$N_k = \sum_{n=1}^{N} r_{nk}, \quad \bar{\mathbf{x}}_k = \frac{1}{N_k}\sum_{n=1}^{N} r_{nk}\mathbf{x}_n,$$

$$\mathbf{S}_k = \frac{1}{N_k}\sum_{n=1}^{N} r_{nk}(\mathbf{x}_n - \bar{\mathbf{x}}_k)(\mathbf{x}_n - \bar{\mathbf{x}}_k)^T.$$

After convergence components that do not take any essential responsibility for explaining the data will have $r_{nk} \simeq 0$ and hence $N_k \simeq 0$.

Fig. 6d demonstrates the result of the sample experimental image clustering by using variational Bayesian GMM approach. The initial values for the parameters are chosen as suggested in [22].

B. Particle-based Tracking

A well-known limitation of the GMM based clustering lies in the mixture parameters initialization procedure: to get good segmentation results we must provide reliable initial conditions; moreover while detecting positions of chicks the clustering provides no information about their behavior in time (tracking). For that reason, it is desirable to combine the clustering with some method able to track chicks by probabilistically integrating all measurements available up to the current time. It was shown that particle filters provide an effective way of sound and visual target tracking [23], [24]. Using a sequential Monte Carlo method, particle filters recursively estimate the probability density of the unknown source state conditioned on all received data up to and including the current frame.

At time t every chick $c = 0, 1, ..., C-1$ is modeled using P particles at positions $\mathbf{x}_{c,p}^{(t)}$, each with its weight $w_{c,p}^{(t)}$. The state vector for particles has four dimensions: two for a position and two for a speed:

$$\mathbf{s}_{c,p}^{(t)} = \begin{bmatrix} \mathbf{x}_{c,p}^{(t)} \\ \dot{\mathbf{x}}_{c,p}^{(t)} \end{bmatrix}.$$

We use the sampling importance resampling algorithm with a predictor in the form, used in [23], as it was shown to work well in practice. The model is defined as

$$\dot{\mathbf{x}}^{(t)} = a\dot{\mathbf{x}}^{(t-1)} + bF_{\mathbf{x}}, \quad \mathbf{x}^{(t)} = \mathbf{x}^{(t-1)} + \Delta T \dot{\mathbf{x}}^{(t)},$$

where $a = e^{-\alpha \Delta T}$, $b = \beta\sqrt{1-a^2}$, $F_{\mathbf{x}}$ is a normally distributed random variable and ΔT is the time interval between two frames. The model parameters suggested in [23] are $\alpha = 0.05$ and $\beta = 0.2$. The positions of chicks, predicted by the filters are used as initial values for means of the Gaussians for the clustering procedure; next we recalculate the weights of particles as follows: $w_{c,p}^{(t)} = e^{-\gamma|\mathbf{x}_{c,p}^{(t)} - \hat{\mathbf{x}}_c^{(t)}|}$, where $\hat{\mathbf{x}}_c^{(t)}$ is a position of c-th chick corrected by GMM clustering. Then the particles are resampled according to their weights, the new set of particles $\mathbf{s}_{c,p}^{(t+1)}$ is predicted by propagating the resampled set according to the dynamical model and the procedure is repeated.

Sometimes it happens that several chicks form a very dense group and the tracker fails to estimate correct number and exact positions of animals, in this case the user can manually correct the tracking results for the problem frames.

VI. EXPERIMENTS

The robotic system is being designed and tested in parallel with behavioral studies on chick groups of domestic fowl. We run various experiments of the following types: 'one chick-one robot', 'several chicks-one robot' and 'several chicks-several robots'. These experiments allow to discover factors influencing the acceptance of the robot by the animals and the relevance of sound and visual communication.

One of the benefit of intelligent autonomous robots is that they allow to repeat many time the same kind of experiments in well controlled trials. These kind of behavioral animal studies are time consuming and heavy work, thus the benefit of having automated intelligent systems is high. For example, it allows us to quantify many behavioral parameters with good metrics and good statistical validity.

To illustrate how the present system can be used in the chicks-robots experiments we will give two examples of experimental data: the individual tests 'one chick-one robot' and the group experiments 'one robot-several chicks'.

A. Individual Experiments

After the imprinting procedure is carried out, every chick is tested to quantify its individual features, i.e. how much it is attracted by the robot depending on the pattern displayed and the kind of call emitted, its exploring preferences of the arena, etc. The same parameters are estimated for the chick in a group and in individual tests. This gives us individual behavioral dynamics characteristics and allows to study the influence of the group mates on the individual preferences.

In individual tests a chick is released into the arena, where the robot executes a random walk behavior with a speed of 8 cm/sec that is comfortable for chicks. In this kind of test we only study the chicks reaction to the robot and don't try to control them to reach a specific goal, so the robot does not react to any cues received from the chicks, it only displays a specific color pattern and emits a call. Then the individual trajectories of the robot and the chicks are extracted from the video records of the trials, and we estimate various parameters, e.g. the amount of time when the chicks were active (the time intervals, when their speed was above a given threshold), the chick-robot distance and the angle between the chick heading direction and the direction from the chick to the robot.

Depending of the demonstrated behavior every chick can be put into one of three groups: *imprinted chicks* that follow the robot; *non imprinted* mainly staying on the spot, where they were released, not paying attention to the robot and sometimes sleeping; and *avoiding* running along the walls as if trying to avoid the robot with a maximal distance. We found that only three behavioral parameters are enough to put any chick into one of these classes with a high level of reliability: a mean chick-robot distance d_m, a mean chick velocity v_m and a mean absolute deviation of the chick velocity vector from the chick-robot vector δ_m. As a classification technique we use the Fisher's linear discriminant. As a training data set we use the results of the individual tests made during one of three experimental series conducted this year (Fig. 7). Been applied to the validation data set corresponding to two other experimental series the classifier managed to put a chick into the correct class in 97% of cases.

B. Group Experiments

Even if the chicks are imprinted on the robot, when in groups they are also attracted by their group mates. In this case the following behavior can be less stable as there is a competition between the attraction to the robot (acting as a leader) and the attraction to other chicks, some of which have a low attraction to the robot. In this kind of experiments, we test various behavioral responses of the robot that would

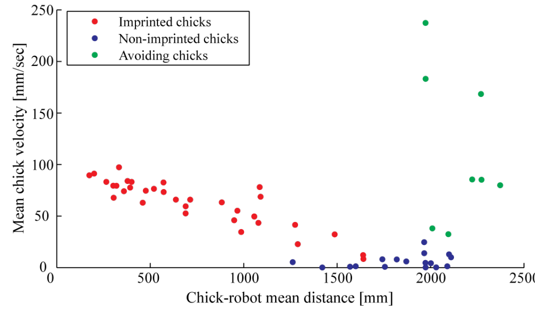


Fig. 7: The d_m-v_m projection of the experimental data for 59 chicks comprising three classes used to train the classifier

increase its leadership on the group. We release one robot and a group of chicks in one corner of the arena, then the robot moves to the opposite corner in order to lead there the group. The vision system provides information about the chicks positions and distance from the robot to the animal group center of mass and the group dispersion. When some parameters are above a threshold, the robot can modify its behavior to attract the group towards its destination like stopping and waiting until chicks join him, or going back to fetch the group, etc. Once reaching the opposite corner the robot rests for a defined duration, then repeats the same procedure. The same experiments can be repeated with the same group, but varying various behavioral parameters in order to quantify the effective leadership of the robot. Fig. 8 presents the robot position on the diagonal line connecting the opposite corners of the arena, superposed with the same value computed for a chick group center of mass. The figure shows that after some initial time the group demonstrates a stable following behavior. In this case the leadership of the robot on the group displacement is efficient.

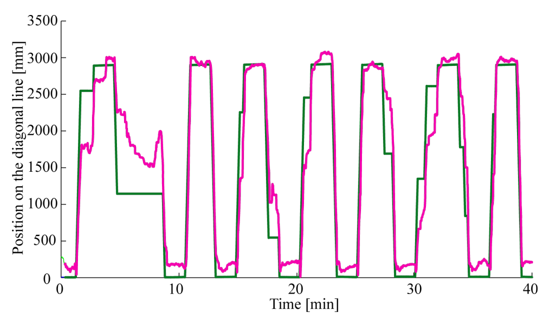


Fig. 8: The position of the robot on the diagonal line (green), superposed with the position of the centre of mass of a chick group (red). The horizontal sections on the robot displacement, which do not correspond to the robot resting in the corner of the arena (maximal and minimal values of the position), mark the situations when robot does not move and waits until chicks join it

VII. CONCLUSIONS AND FUTURE WORKS

In this paper, we have presented a set of tools for the experimental study on interaction between chicks and robots in mixed groups – the PoulBot mobile robot, the audio-visual monitoring and recording system and the visual data analysis system.

At the present stage we have shown that the robot can be accepted by chick groups using the filial imprinting learning process modulated by the patterns that are displayed by the robot and its sound emission. Thanks to the tracking tools we are able to quantify the strength of the imprinting and hence the level of leadership the robot has on the chicks. It also allows us to quantify both the individual and the group behavior and to study the impact of the individual behavioral parameters on the collective level. In future work we will concentrate on further development of the experimental setup by adding specific sensors and actuators such as feeders and humidity and temperature sensors as well as on the PoulBot robot, providing the robot with the hardware and software extensions to carry out more complex interactions with the chicks and to control a wider range of behaviors. The use of the robot allows to carry out experiments that are very difficult or even impossible to do with natural hens. For example, since the pattern displayed by the robot is dynamic, we will be able to study the cognitive processes of pattern recognition in chicks. The sound perception system can detect the origin and location of sound calls emitted by the chicks. The robots would then adapt their behavior according to this sound perception. The next step will be to analyze the sound calls and to categorize them according to the chicken vocal repertoire. This will allow the robot to respond appropriately to specific calls like, for example, distress calls. This experimental approach will be useful to entangle the impact of the various cognitive and communication processes on collective behavior.

We have experimentally verified the applicability of our system in scientific experiments to study animal social behavior. As it is possible to change the behavioral models and parameters of the robots, various hypotheses can be tested. After behavioral models are build and validated, it is possible to implement them in the robot to control the whole group behavior by interacting with the animals [6]. This form of modulation or control is based on the natural behavior observed and will take into account animal natural constraints and welfare.

Moreover, one of the forthcoming challenges will be to build cognitive processes performed by the robot to be able to establish cooperation with animals. The advantage of this approach is that a form of AI has to be developed in a real application context with clear metrics provided by collective behavioral tests allowing to assess its success. The comparison between the kind of AI performed by the robot and the kind of animal intelligence in presence is direct. This line of research could produce a framework for designing hybrid collective intelligence between natural and artificial systems. We will speculate about designing cooperation in mixed societies of animals and robots that will produce novel collective intelligence in which the animals and robots make use of their respective and different capabilities and enhance the global performance of the group. Furthermore, on the long term, the results obtained in our studies could become the foundation to design novel intelligent robotic system based on natural behaviors and used in farming to improve breeding conditions of poultry.

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