Plastic 'personalities' for effective field swarms

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***Abstract*—Most studies on real-world multi-robot systems have been performed in controlled laboratory environments, whereas the real world is unpredictable and sometimes hazardous. I have recently suggested that the natural phenomenon of *phenotypic plasticity* provides a useful bioinspiration framework for making such systems more resilient in field conditions [1]. Phenotypic plasticity occurs when a single genotype produces a range of phenotypes (observable traits) in response to different environmental conditions. Consistent individual behavioural differences can result from such plasticity, and have been described as 'personalities'. At the same time, in social animals, individual heterogeneity is increasingly recognised as functional for the group. We can exploit this functional heterogeneity as engineers trying to design field robot systems, and phenotypic plasticity can provide meaningful diversity 'for free', based on the local experience of agents. Personality axes such as bold–shy or social–asocial can be represented as single variables, with the advantage of being transparent and intuitive for human users, and predictable in their effects. For example, in a dangerous environment, robots may become more 'shy' and 'social' to stay closer together and out of harm's way.**

***Index Terms*—phenotypic plasticity, reaction norms, resilience, personality, functional heterogeneity, field robotics**

I. Introduction

There is increasing recognition in biology that consistent individual differences in behaviour ('personality') among group members can be important for group function in local ecologies [2]. Examples of significant personality axes include: risk-taking behaviour (boldness—shyness), exploratory behaviour (neophilic—neophobic), activity levels (active—inactive), sociability (social—asocial), and aggression (aggressive—non-aggressive) [3]. Variation can also be seen in reaction threshold-type behaviours, for example the acceptability of options in a decision task [4]; one might term this 'choosiness' or 'pickiness'. Despite the definition of personality relating to *consistent* differences, personality is also recognised as being somewhat variable – plastic – over time.

The term *developmental reaction norm* (DRN) describes the range of phenotypes generated by a given genotype (artificial agent controller) in response to experienced environmental cues [5]. There are at least five attributes to DRNs: amount of plasticity (large/small); pattern of response (e.g. monotonic increase/decrease or more complex reaction curves); rapidity of response; reversibility of response; and competence (possibility) of the developmental system to respond at a certain stage in an organism's (agent's) lifetime [5]. One can refer to *behavioural reaction norms* (BRNs) if behaviour is the focus, as is the case here (plasticity can also be observed in physiology and morphology). BRNs can be a useful framework for integrating the notions of animal personality and individual plasticity [6]. In biology, the various attributes of developmental reaction norms are, in principle, subject to natural selection [5], [6]. I suggest that engineers attempting to deploy collectives of robots into real-world field conditions can undertake pre-deployment artificial evolution of DRNs. This should establish an adaptive DRN profile [1].

Examples of personality variation can be readily found at the level of the individual or the whole group, which gives rise to the notion of collective personalities [7]. Behavioural plasticity allows organisms to make relatively rapid adjustments in their function to adapt to changing environmental conditions, and can be seen as personality adaptation [6]. This is true for individuals, and also for whole groups: for instance, in leaf-cutter ants the whole colony can become more threat-responsive and aggressive in response to disturbance [8].

II. Personality plasticity as complementary to existing approaches

There are already several examples in the swarm robotics literature in which individual robots, though identically programmed with the same controller, end up behaving differently according to their experience of the environment. These are briefly:

- Off-line (pre-deployment) evolutionary optimisation to identify environmentally contingent behaviours that are adaptive at the group level (e.g. [9]); though effectiveness is tuned to the particular simulated environment.
- With sufficient computing power, one can undertake on-line (on-deployment) evolutionary optimisation (e.g. [10]). However, evolutionary approaches (off- or on-line) could struggle in the field owing to unanticipated circumstances or because of the 'reality gap' between the world and (inner) simulation (e.g. [11]).
- On-deployment learning: typically this employs (evolved) neural networks (e.g. [12]). Yet, neural network-based approaches can have difficulty in scaling to more complex problems [13] and be less human-readable.

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I suggest 'personality' adaptation can be an effective, minimal bio-inspired approach to learning, suitable for unpredictable real-world environments and potentially complementary to the above approaches. The notion of personality maps readily to adaptive threshold-based behaviours: for example, the likelihood of switching behaviours in probabilistic finite state machines (e.g. [14]). Animal personality research can indicate simple behavioural mechanisms ('interaction rules') that adaptively shape personality. For example, the frequency of social interactions can relate to boldness changes [15]. Such rules can be transposed into embodied and/or virtual artificial agents working in collectives. Principle advantages of this approach could include:

- Various major personality axes could be relevant to groups of field robots, and these can each be represented as a single variable.
- Personality variables can adapt quickly and predictably to changing environments.
- The notion of personality is intuitive for human users.
- Individual experience of the environment will lead to a certain amount of group-level diversity in personality variables, the advantages of which I outline in Section III.

Plasticity occurs in response to local environmental cues, so one must also consider the relevant environmental features (physical and social) that will elicit change – and how they will be sensed. For example, one may wish to use agent density as a proxy for group size. This could be sensed via frequency of physical interactions, which in turn could be correlated with risk-taking behaviour [15], if one prefers individuals in larger groups to take on a higher risk appetite.

III. Advantages of behavioural diversity

A group of identically-programmed (homogeneous) agents deployed into a variable (heterogeneous) environment will each experience different conditions, to a greater or lesser extent. Each may benefit from individual adaptation; or indeed, individual differences may occur which have little significance when considered in relation to the *direct* 'fitness' of a single individual. Nevertheless, at the level of the collective, such heterogeneity may make an important indirect contribution to the fitness of the swarm, as part of an adaptive collective phenotype [16]. As such, the group-level distribution of personality traits may be self-organized through interactions with the environment and others to favour a certain ecologically relevant pattern [15], as I go on to illustrate.

A. Animal collectives

1) Diversity for decision-making: Autonomous collectives – whether in biology, robotics or elsewhere – need to be capable of making collective decisions. Diversity of reaction thresholds or option assessment behaviour, as seen in ants, can help this process [4], [17]. As an example of this, a proportion of individuals with high acceptance thresholds may reject medium-quality options, and thus through continued exploration go on to discover higher-quality possibilities.

2) Diversity for homeostasis: In biological systems phenotypic diversity can also promote positive collective success: for example, in honeybees diversity in reaction thresholds for their cooling behaviour promotes stability in nest thermoregulation [18]. Although this example is driven by corresponding genetic heterogeneity, it could equally be designed in an artificial agent context to result from phenotypic plasticity.

In *Stegodyphus* social spiders the group-level distribution of boldness is important for their collective predation performance [19]. Thus, one expects some form of mechanism to maintain a suitable collective boldness phenotype, and indeed there is evidence for a link between social interactions and boldness change to achieve this via self-organization [15].

3) Diversity as a shield against adversity: Inbreeding in agriculture is observed as a cause of disease vulnerability, because a single pathogen virulent against one individual can quickly spread across the whole population; conversely, diversity can help resistance [20].

Similarly, robustness is frequently claimed for swarm robot systems, but if a homogeneous controller results in homogeneous behaviour it may be liable to systematic failure if the swarm encounters unexpected environmental conditions or faulty or malicious agents.

4) Diversity for foraging and search: Variation in individual behaviour can also be important for effective foraging and search, as demonstrated for example by Fricke et al. in immune-system-inspired search algorithms [21]. If search targets have heterogeneous configurations (for example, sometimes low density, other times high density) a collective of agents will be more effective if individuals behave differently.

B. Human teams

There is evidence that teams with more diverse personality types are more effective: for example, Mohammed & Angell found that higher variability in extraversion results in higher task performance [22]. In this context I suggest that there are opportunities to enhance collective intelligence in human-AI interaction. Virtual agents and robots could benefit from suitably plastic personalities to adapt and complement the shortcomings or absence of relevant behavioural types in their human teams. This could be done as virtual team members or as adaptive social assistance robots [23], working as facilitators, contributing to a successful 'hybrid' team phenotype.

IV. Conclusions

As we deploy robots into real-world field conditions, equipping them with smart behavioural reaction norms – *plastic personalities* – could help them to work effectively in unpredictable conditions: individually, and as a a team. Advantages could include simplicity (single personality variables), transparency, intuitiveness, predictability, and automatic diversity in multi-robot teams from local experience. Future work will focus on demonstration of these concepts in simulation, before experiments on real world platforms such as unmanned ground vehicles (UGVs) undertaking tasks such as search and decision-making in unpredictable environments.

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