Article:

Collective Decision-Making

Thomas Bose[1], Andreagiovanni Reina[1], James A. R. Marshall[1,2]

[1]Department of Computer Science and [2]Department of Animal and Plant Sciences

University of Sheffield

Regent Court

211 Portobello

Sheffield S1 4DP

UNITED KINGDOM

Abstract:

! "#$%&'($)*$%'+'"', -. /0', 1 is the subfield of collective behaviour concerned with how groups reach decisions. Almost all aspects of behaviour can be considered in a decision-making context, but here we focus primarily on how groups should optimally reach consensus, what criteria decision-makers should optimise, and how individuals and groups should forage to optimise their nutrition. We argue for deep parallels between understanding decisions made by individuals and by groups, such as the decision-guiding principle of (/#2$-+$, +'&'('&3. We also review relevant theory and empirical development for the study of collective decision making, including the use of robots.

We consider collective decision-making to be the subfield of collective behaviour concerned with how groups reach decisions without centralised leadership. Examples include nestsite selection by honeybees [1] and ants [2], and consensus selection of food sources in shoaling fish [3]. Individuals in a group can prefer to participate in a consensus decision, in which all individuals seek to agree on the same outcome, either because the group is tightly functionally integrated, nnJlJMvggia sZı 'a srnigR.vl.rvMJig.gRRigahsArniia sZı MJrng.ll.ilalsArn

34 relatedness groups under appropriate conditions, selection on the group can

35 lead to group-level adaptations [4] , so group members' behaviour is shaped as

36 part of a group-level decision-making mechanism. Within unrelated groups,

37 individuals' behaviour should maximise their own expected fitness, within the

38 context of the group [5]. Indeed inferring 'group cognition' abilities for unrelated

39 groups may be harder than previously appreciated; alternative explanations for

40 improved decision performance in fish shoals are that fish in larger groups have

41 improved individual-level abilities, and that larger groups are more likely to

42 contain better decision-makers who dominate collective decisions [6].

43　　　　In this review we focus primarily on functionally-integrated decision-

44 making systems for two reasons; first, as mentioned above, functional group

45 integration makes it appropriate to apply **"4&'. /#'&3)&5$"63** at the level of the

46 group [7]. Second, parallels can be drawn between the behavioural rules of a

47 'superorganismal' group, and the behavioural rules of unitary individuals. We

48 consider such parallels to be illuminating. Our review can thus be read as

49 primarily presenting an 'economic' view of the behaviour of groups making

50 decisions, where decision outcomes result in gains or losses of quantities that co-

51 vary with reproductive fitness. We place particular emphasis on the links

52 between collective decision-making, perceptual decision making and value-

53 based decision-making, and on nutritional decision-making. We review

54 applicable theory, as well as the emerging use of robotics, for understanding

55 such systems.

56

57

58　　　　Groups can realise superior decision performance to individuals for a

59 variety of reasons. The simplest argument is based on the 'wisdom of the

60 crowds', recognised since the early 20th Century; for example a group decision

61 realised by pooling independent individual assessments will be more accurate

62 than an individual group member, under certain reasonable assumptions [8].

63 Inevitably, further refinements of group decision-making are possible; here we

64 mention two recent developments.

65　　　　**7'1, /#)*$&$%&'",)&5$"63**, developed to understand optimal psychophysical

66 decision-making by individuals, shows that there is an inherent decision-making

67   trade-off between true positive rate and false positive rate; a decision-maker

68   cannot improve the rate at which they detect events of interest, without also

69   increasing the rate at which they incorrectly detect those events when they have

70   not happened. Yet in the group situation, Max Wolf and colleagues show how

71   introducing a quorum decision rule, typical of social insect colonies, allows the

72   group to simultaneously improve both rates [9]. Understanding how to correctly

73   set quorums, which may be sub-majority or super-majority according to the

74   accuracy of individuals, also shows that in fact group decisions are /#8/3+ more

75   accurate than individual decisions [10].

76   Still further improvement is possible on group decision-making, by

77   accounting for the unavoidable variation in individual decision accuracy.

78   Decision theory shows how to optimally weight individuals' contributions to

79   group decisions according to their accuracy, or 'confidence'; this theory has been

80   applied successfully to human groups and may be fruitfully applied to other

81   animal groups [11].

82

83

84   In the preceding section group decision performance was considered in

85   terms of decision accuracy, or probability of making the correct response. Yet

86   consider the decision problem faced by a honeybee swarm selecting a new nest

87   site [12]. Obviously, it is advantageous for the collective of bees to choose the site

88   of highest possible quality. Imagine, for example, that there are two potential

89   nestsites available, both of equal but low quality. In this case it is best to wait and

90   postpone the decision until another option will be discovered. In contrast, if

91   there are two alternatives having equal but high qualities, then the honeybees

92   should choose as quickly as possible, as a long decision making process is

93   accompanied by the consumption of resources and a prolonged absence of

94   shelter, and does not lead to any further advantage.

95   Precisely such an adaptive value-sensitive decision making mechanism

96   has been analysed in a model of the stop-signalling behaviour of honeybees [12],

97   whose decision dynamics change adaptively as a function of quality of available

98   options [13,14]. In case of equal, high quality options a lower cross-inhibition

99   strength is sufficient to break decision deadlock compared to higher cross-

100   inhibition strengths required for lower quality options [13]. This has led to the

101   proposal of a +4$$*-(/#2$)&6/*$"99 [15] that underlies value-based decisions,

102   rather than a +4$$*-/%%26/%3)&6/*$"99 as discussed in the preceding section, and

103   considered in conventional two-alternative choice perceptual decisions [16].

104   Conceptualising value-based decisions shows, however, that there are

105   similarities between perceptual and value-based decision making [17,18],

106   although the usage of the term 'value' may vary with context [19]; value may

107   refer to stimulus intensity, or to reward magnitude. In fact, recent studies

108   demonstrate that for primates value-sensitivity represents an important feature

109   of perceptual decision making, underlining the significance of absolute values

110   (magnitudes) of input signals [20]. Teodorescu et al. showed in experiments with

111   human participants that increasing the magnitudes of two input signals while

112   keeping their difference or ratio constant leads to faster responses; this effect is

113   not predicted by influential decision models that optimise the speed-accuracy

114   trade-off. Using data from humans and monkeys, similar observations are

115   reported by Pirrone et al. [21] for the case of equal alternatives for both

116   perceptual decisions where 'value' represents the magnitude of an input signal,

117   and value-based decisions where 'value' denotes a reward. These results provide

118   evidence for a speed-value tradeoff in decision making and, given the suggested

119   similarities between decision making in the brain and collective decision making

120   in social insects (e.g. see [7,22]) may provide new insights into the underlying

121   principles of collective decision making in social groups. Speed-value trade-offs

122   should be as fundamental for groups as they are for individuals.

123   A speed-value tradeoff should play a key role in decision making that is

124   not about 'correct' or 'false' but rather requires a strategy to choose the best

125   alternative among available options. Therefore, it would be interesting to

126   investigate the link between speed-value tradeoffs and a recently published

127   model describing the optimal decision making strategy for value-based decisions

128   [23], which may reflect the ultimate goal of maximising fitness and reproductive

129   success in realistic natural decision making scenarios, including collective

130   decision making of insect societies.

131

132

133

Individuals on their own or within social groups frequently make foraging decisions. Those decisions often aim at balancing the intake of different nutrients rather than maximising the gain in energy [24], as described by the : $''. $&6'%) ;6/. $8''60 — a graphical approach pioneered by Stephen Simpson and David Raubenheimer [24,25]. In this framework, the performances of animals or insect colonies are evaluated by considering their actions in , 2&6'$, &)+4/%$. The geometric framework is important for functionally-integrated social insects colonies as for single animals, as satisfying nutritional needs is crucial for both. Thus, nutritional deficits may bias or shape decision making for both in a similar way. The nutrient space is an N-dimensional space, which is spanned by N axes each of which represents one nutrient required in the diet. Imagine, for example, an animal or social insect colony that needs to consume proteins and carbohydrates. Then, the nutrient space is two-dimensional. The performance of the animal or social insects can then be evaluated by plotting the deficits in proteins and in carbohydrates on the axes of a two-dimensional Cartesian coordinate plane. As the aim of the (super)organism is to reach a nutritional target [25], a measure of distance between current state (a point in the diagram) and target (another point) quantifies the effectiveness of their foraging behaviour. When nutrients do not interact this required distance measure is simply Euclidean distance [25].

Although based mostly on laboratory experiments, considering two-dimensional problems such as choosing between proteins and carbohydrates, or food and water, has led to important insights into how animals and social groups forage and is empirically well motivated [24,26–29]. Given a)target intake the animal or the insect colony has to fulfil an ongoing decision task by selecting repeatedly among two alternatives, to bring their internal state as close as possible to their target intake. Hence, behaviour that is guided by multiple decisions can be tracked in nutrient space. Deficits in one or more nutrients drive the motivations for deciding for or against an action that reduces a deficit. Houston et al. analyse the optimal strategy for reducing expected deficit in simple scenarios where food types contain differing ratios of required nutrients [30]; the optimal strategy requires decision-makers to reach a switching line and

166   then move along this by ingesting food items in the required ratio. This is hard

167   for animals to do without incurring switching costs, which change the optimal

168   strategy [29], but could be more readily achieved by a social insect colony, or

169   similar, regulating nutrient intake via a population of foragers.

170   The geometric framework has been studied in decentralised decision-

171   making systems such as ant colonies [27] and slime molds [26]. Nutrition in ants

172   is particularly well studied and emphasises the insect group's cognitive ability to

173   integrate the different nutritional needs of workers and larvae [27], and the

174   flexibility to make decisions in dynamic environments [31], whilst also

175   highlighting the vulnerability to extreme nutritional imbalances [32].

176   Considering the foraging decisions of ant colonies illustrates the social

177   dimension of nutrition [33] and has been related to social immunity [34]. This

178   link between nutrition and immunocompetence has also been observed in

179   honeybees [35].

180   Being central to all social groups, nutritional interactions may have

181   contributed to the evolution of social behaviour [36]. In this light, recent

182   observations in wasps [37] showing reductions in mushroom body investments

183   from solitary to social species indicate the intriguing connection between

184   'distributed cognition' [37], sociality and nutritional decision making by social

185   insect colonies in evolutionary contexts. It could be interesting to see what

186   effects imbalanced nutrition has on non-foraging decisions of social insects, such

187   as in the house hunting of honeybees. Here, the geometric framework could be

188   used to characterise the nutritional state of the colony, providing the link

189   between nutrient regulation at multiple organisation levels, social immunity,

190   cognitive abilities in general and collective decision making in particular.

191

192

193   For several decades, solutions from nature have been taken as a source of

194   inspiration for the design of robotic systems. This is particularly true for the field

195   of +8/6.)6''<''&'%+, where a large number of autonomous robots coordinate with

196   each other to perform a common task. In these decentralised systems, each

197   individual gathers and exchanges information with the environment and peers in

198   a local range; the large number of individuals and nonlinear interactions lead to

199 a coordinated collective response of the swarm. Given the difficulties in

200 identifying the rules that each agent should follow in order to obtain the desired

201 collective behaviour, a widespread approach has been to look at natural

202 processes that display the desired behaviour and adapt such processes to

203 implement multirobot systems.

204 While most works have an engineering scope a few robotics studies,

205 instead, aim at replicating the actual animal behaviour to investigate the veracity

206 of different assumptions, or validate the correctness of biological models (e.g.,

207 [38,39]). Usually, to understand collective processes biologists use analytical and

208 computational models such as multiagent simulations, in order to identify

209 individual rules that lead to the observed group response. Through models, the

210 individual behaviour can be varied systematically to identify which are the

211 relevant components or model parameters. In collective behaviour, the process

212 dynamics are principally determined by how information is acquired, processed

213 and transferred between individuals. In some cases, all relevant components and

214 realistic assumptions can be included in the mathematical model. However,
when space, situatedness

229   with each other [41,43–45]. The first challenge of this research field concerns the

230   design of robots that are considered as groupmates by the animals. These studies

231   allow identification of the relevant perceptual components used by the animals

232   (e.g., robot-fish [46–48], robot-bee [49], robot-rat [50]). Once a robot is accepted

233   as a groupmate, controlling the robot's behaviour allows investigation of social

234   interactions and how animals respond to specific behaviours. These studies help

235   to identify individuals' cognitive abilities [45,51–53] as well as how (and what)

236   information is transferred within groups [54,55].

237

238

239   As motivated in the Introduction, our review has focussed primarily on an

240   economic view on collective decision-making. The economic view is a staple of

241   behavioural ecology, and motivates the tools of optimal decision theory for the

242   study of animal behaviour. Here we argue that for decisions in functionally-

243   integrated groups, such as social insect colonies, optimality theory should also be

244   applied to collective behaviour. The economic, optimality theory, view is also

245   applied extensively to understanding animal behaviour in the various fields of

246   neuroscience and psychology. There, the additional focus on mechanisms

247   underlying behaviour opens up a new dimension of study. In studying individual

248   animal behaviour, behavioural ecology has traditionally ignored mechanism,

249   however there is a movement to integrate the study of mechanism with function

250   [56]. Collective behaviour is, of course, particularly amenable to observation of

251   mechanisms. Furthermore, through adopting modern robotics technology,

252   behavioural mechanisms can be elucidated through manipulation; this might be

253   of particular interest in functionally-integrated decision-making groups such as

254   social insect colonies. We argue that when drawing parallels between

255   mechanisms for collective behaviour and mechanisms for individual behaviour is

256   justified, doing so provides a particularly powerful research programme.

257

258

262

263

1. Seeley TD: **?'', \$3<\$\$)@\$. ''%6/%3**. Princeton University Press; 2010.

2. Sasaki T, Pratt SC: **Groups have a larger cognitive capacity than individuals**. !266)A'''#= 2012, **22**:R827–R829.

3. Couzin ID, Ioannou CC, Demirel G, Gross T, Torney CJ, Hartnett A, Conradt L, Levin SA, Leonard NE: **Uninformed Individuals Promote Democratic Consensus in Animal Groups**. 7%'\$, %\$ 2011, **334**:1578–1580.

4. Bourke AFG: B6', %'4#\$+)''9)7''%'/#)C(''#2&''', . Oxford University Press; 2011.

5. Marshall JAR: 7''%'/#)C(''#2&''',)/, *)D, %#2+'(\$); '&, \$++)E5\$''63F)G,) D, &6''*2%&''', . Princeton University Press; 2015.

6. Ioannou CC: **Swarm intelligence in fish? The difficulty in demonstrating distributed and self-organised collective intelligence in (some) animal groups**. A\$5/(-)B6''%\$++\$+ 2016, doi:10.1016/j.beproc.2016.10.005.

7. Marshall JAR, Bogacz R, Dornhaus A, Planqué R, Kovacs T, Franks NR: **On optimal decision-making in brains and social insect colonies**. ⫪)⎜-)7''%-)D, &\$69/%\$ 2009, **6**:1065–74.

8. King AJ, Cowlishaw G: **When to use social information: the advantage of large group size in individual decision making**. A'''#-)J\$&&= 2007, **3**:137–139.

9. Wolf M, Kurvers RHJM, Ward AJW, Krause S, Krause J: **Accurate decisions in an uncertain world: collective cognition increases true positives while decreasing false positives**. B6''%-)⎜-)7''%-)A. 2013, **280**:20122777.

10. Wolf M, Kurvers RHJM, Krause J, Marshall JAR: **Collective intelligence: when and how to pool independent judgements**. D,)46\$4=

11. Marshall JAR, Brown G, Radford AN: **Individual Confidence-Weighting and Group Decision-Making**. D,)46\$4.

12. Seeley TD, Visscher PK, Schlegel T, Hogan PM, Franks NR, Marshall JAR: **Stop signals provide cross inhibition in collective decision-making by honeybee swarms**. 7%'\$, %\$ 2012, **335**:108–11.

13. Pais D, Hogan PM, Schlegel T, Franks NR, Leonard NE, Marshall JAR: **A Mechanism for Value-Sensitive Decision-Making**. BJ''7)K, \$ 2013, **8**:e73216.

14. Reina A, Marshall JAR, Trianni V, Bose T: **A model of the best-of-N nest-site selection process in honeybees**. arXiv:1611.07575v1 [physics.bio-ph] 2016.

15. Pirrone A, Stafford T, Marshall JAR: **When natural selection should optimize speed-accuracy trade-offs**. ⫲6'', &-)L\$26''+%'= 2014, **8**:1–5.

16. Bogacz R, Brown E, Moehlis J, Holmes P, Cohen JD: **The physics of optimal decision making: A formal analysis of models of performance in two-alternative forced-choice tasks**. B+3%5''#)⎜ \$(= 2006, **113**:700–765.

17. Sugrue LP, Corrado GS, Newsome WT: **Choosing the greater of two goods: neural currencies for valuation and decision making**. L/&-)⎜ \$(-) L\$26''+%'= 2005, **6**:363–375.

18. Bastest 6, Tai⫲⎜e&, eTelⶣ6sⴽrⵍⵎⵏ, iⴿⵆⴽⵏ⫲sⵆrⵏⶣⵍⵍ6sⵃrgⵍⶣl 3⫲il3r;⵮8⵲ ⵏⵍ *lⵍgⵏⵃⵎTⴽⵍga ⵜⵍⵍnⵏⵥⵍⵍⵉ

310 19. Rangel A, Camerer C, Montague PR: **A framework for studying the neurobiology of value-based decision making**. L/&)l $(-)L$26"+%'=2008, **9**:545–556.

313 20. Teodorescu AR, Moran R, Usher M: **Absolutely relative or relatively absolute: violations of value invariance in human decision making**. B+3%5",)A2##)l $(=2016, **23**:22. doi:10.3758/s13423-015-0858-8.

316 21. Pirrone A, Azab H, Hayden BY, Stafford T, Marshall JAR: **Evidence for the speed-value trade-off: human and monkey decision making is magnitude sensitive**. @$%'+'", 2016, ',)46$++.

319 22. Couzin ID: **Collective cognition in animal groups**. E6$, *+)! "1,)7%'=2009, **13**:36–43.

321 23. Tajima S, Drugowitsch J, Pouget A: **Optimal policy for value-based decison-making**. L/&)! ". . 2, =2016, **7**:12400. doi:10.1038/ncomms12400.

324 24. Simpson SJ, Sibly RM, Lee KP, Behmer ST, Raubenheimer D: **Optimal foraging when regulating intake of multiple nutrients**. G, '.)A$5/(= 2004, **68**:1299–1311.

327 25. Simpson SJ, Raubenheimer D: E5$)L/&26$)"9)L2&6'&'", lf)G)N, '93', 1) ;6/. $8"60)%6".)G, '. /#)G*/4&/&'",)&'")?2. /,)K<$+'&3. Princeton University Press; 2012.

330 26. Dussutour A, Latty T, Beekman M, Simpson SJ: **Amoeboid organism solves complex nutritional challenges**. B6"%-)L/&#)G%/*-)7%')N-)7)G=2010, **107**:4607–11.

333 27. Dussutour A, Simpson SJ: **Communal Nutrition in Ants**. ! 266)A'"#=2009, **19**:740–744.

335 28. Houston AI, Higginson AD, McNamara JM: **Optimal foraging for multiple nutrients in an unpredictable environment**. C%"#)J$&&=2011, **14**:1101–1107.

338 29. Marshall JAR, Favreau-Peigne A, Fromhage L, McNamara JM, Meah LFS, Houston AI: **Cross inhibition improves activity selection when switching incurs time costs**. ! 266)0""#=2015, **61**:242-250.

341 30. Houston A, Sumida B: **A positive feedback model for switching between two activities**. G, '.)A$5/(=1985, **33**:315–325.

343 31. Dussutour A, Nicolis SC: **Flexibility in collective decision-making by ant colonies: Tracking food across space and time**. ! 5/"+P)7"#'&", +)Q) ;6/%%/#+ 2013, **50**:32–38.

346 32. Dussutour A, Simpson SJ: **Ant workers die young and colonies collapse when fed a high-protein diet**. B6"%-)l)7"%-)A 2012, **279**:2402-2408.

348 33. Lihoreau M, Buhl J, Charleston MA, Sword GA, Raubenheimer D, Simpson SJ: **Modelling nutrition across organizational levels: From individuals to superorganisms**. lf)D, +$%&)B53+'"#=2014, **69**:2–11.

351 34. Kay AD, Bruning AJ, van Alst A, Abrahamson TT, Hughes WOH, Kaspari M: **A carbohydrate-rich diet increases social immunity in ants**. B6"%-)l) 7"%-)A 2014, **281**:20132374.

354 35. Alaux C, Ducloz F, Crauser D, Le Conte Y: **Diet effects on honeybee immunocompetence**. A'"#-)J$&&=2010, **6**:562–5.

356 36. Reade AJ, Naug D: **Inter-individual variation in nutrient balancing in the honeybee (Apis mellifera)**. lf)D, +$%&)B53+'"#=2016, **95**:17–22.

358 37. O'Donnell S, Bulova SJ, DeLeon S, Khodak P, Miller S, Sulger E: **Distributed**

359   **cognition and social brains: reductions in mushroom body**
360   **investment accompanied the origins of sociality in wasps**
361   **(Hymenoptera: Vespidae)**. B6"%)l]7"%)A 2015, **282**:20150791.
362   38.   Webb B: **Cognition in insects**. B5'#)E6/, +)l]7"%)A 2012, **367**:2715–2722.
363   39.   Wischmann S, Floreano D, Keller L: **Historical contingency affects**
364   **signaling strategies and competitive abilities in evolving populations**
365   **of simulated robots**. B6"%)L/&#)G%/*]7%'=2012, **109**:864–868.
366   40.   Garnier S: **From ants to robots and back: how robotics can contribute**
367   **to the study of collective animal behavior**. In A'"-D, +4'6$*)7$#9-
368   K61/, 'R', 1)l "<"&'%)73+&$. +. . Springer; 2011:105–120.
369   41.   Mitri S, Wischmann S, Floreano D, Keller L: **Using robots to understand**
370   **social behaviour**. A'"#)l $(=2013, **88**:31–39.
371   42.   Trianni V, De Simone D, Reina A, Baronchelli A: **Emergence of Consensus**
372   **in a Multi-Robot Network: from Abstract Models to Empirical**
373   **Validation**. DCCC)l "<"&)G2&".]J$&&=2016, **1**:348–353.
374   43.   Krause J, Winfield AFT, Deneubourg J-L: **Interactive robots in**
375   **experimental biology**. E6$, *+)C%"#)C("#=2011, **26**:369–375.
376   44.   Klein BA, Stein J, Taylor RC: **Robots in the service of animal behavior**.
377   !". . 2,]D, &$16)A'"#=2012, **5**:466–472.
378   45.   Frohnwieser A, Murray JC, Pike TW, Wilkinson A: **Using robots to**
379   **understand animal cognition**. H)C>4)G, /#)A$5/(=2016, **105**:14–22.
380   46.   Du R, Li Z, Youcef-Toumi K, Valdivia y Alvarado P: l "<"&); '+5F)A'"-', +4'6$*)
381   ; '+5#'0$)N, *$68/&$6)l "<"&+. Springer-Verlag Berlin Heidelberg; 2015.
382   47.   Landgraf T, Bierbach D, Nguyen H, Muggelberg N, Romanczuk P, Krause J:
383   **RoboFish: increased acceptance of interactive robotic fish with**
384   **realistic eyes and natural motion patterns by live Trinidadian**
385   **guppies**. A'"', +4'6)A'". '. =2016, **11**:15001.
386   48.   Bartolini T, Mwaffo V, Showler A, Macrì S, Butail S, Porfiri M: **Zebrafish**
387   **response to {3D} printed shoals of conspecifics: the effect of body**
388   **size**. A'"', +4'6)A'". '. =2016, **11**:26003.
389   49.   Landgraf T, Rojas R, Nguyen H, Kriegel F, Stettin K: **Analysis of the**
390   **Waggle Dance Motion of Honeybees for the Design of a Biomimetic**
391   **Honeybee Robot**. BJ"7)K, $ 2011, **6**:1–10.
392   50.   Shi Q, Ishii H, Kinoshita S, Takanishi A, Okabayashi S, Iida N, Kimura H,
393   Shibata S: **Modulation of rat behaviour by using a rat-like robot**.
394   A'"', +4'6)A'". '. =2013, **8**:46002.
395   51.   de Margerie E, Lumineau S, Houdelier C, Yris M-AR: **Influence of a mobile**
396   **robot on the spatial behaviour of quail chicks**. A'"', +4'6)A'". '. =2011,
397   **6**:34001.
398   52.   Clark DL, Macedonia JM, Rowe JW, Stuart MA, Kemp DJ, Ord TJ: **Evolution**
399   **of displays in Galápagos lava lizards: comparative analyses of**
400   **signallers and robot playbacks to receivers**. G, '.]A$5/(=2015,
401   **109**:33–44.
402   53.   Butler SR, Fernández-Juricic E: **European starlings recognize the**
403   **location of robotic conspecific attention**. A'"#)J$&&=2014, **10**.
404   54.   Butail S, Abaid N, Macrì S, Porfiri M: **Fish--Robot Interactions: Robot**
405   **Fish in Animal Behavioral Studies**. In l "<"&); '+5F)A'"-', +4'6$*); '+5#'0$)
406   N, *$68/&$6)l "<"&+. Edited by Du R, Li Z, Youcef-Toumi K, y Alvarado P.
407   Springer Berlin Heidelberg; 2015:359–377.

408   55.   Kopman V, Laut J, Polverino G, Porfiri M: **Closed-loop control of**
409   **zebrafish response using a bioinspired robotic-fish in a preference**
410   **test**. ⊩)Ɩ ∋7"‰)Ɒ, &$69/%$ 2013, **10:20120540**.
411   56.   McNamara JM, Houston AI: **Integrating function and mechanism**. Ɛ6$, *₊)
412   C%"#)C("#∈ 2009, **24**:670–675.

413

414

415

416   ¥   Wolf, Kurvers, Krause, Marshall (2016) - ** In this paper the authors

417   demonstrate how group decisions are always more accurate than

418   individual decisions, yet achieving this improvement requires that

419   quorum thresholds for decisions be set according to the accuracy of group

420   members, and optimal thresholds need not be simple majority rules.

421   ¥   Marshall, Brown, Radford (2016) - ** In this review the authors note that

422   when group members vary in individual decision accuracy, decision

423   theory shows how contributions to group decisions should be weighted

424   by the accuracies, or confidences, of group members. The authors review

425   the application of such theory to human collective decision-making and

426   note the potential for application of the theory to non-human animal

427   groups.

428   ¥   Teodorescu, Moran, Usher (2016) - ** This paper demonstrates the

429   presence of magnitude sensitivity in decision making by individuals. The

430   authors show that the absolute value of a stimulus does matter in decision

431   making, as an increase of the absolute value reduces decision times, in

432   agreement with theoretical arguments [13,15] . The authors emphasise

433   that theoretical frameworks explaining decisions only based on the

434   accumulation of relative evidence cannot explain experimental findings

435   and they propose two alternatives to resolve this issue, one being based

436   on a drift diffusion model with value-dependent multiplicative noise and

437   the other one being related to a leaky competing accumulator model with

438   lateral inhibition.

439   ¥   Tajima, Drugowitsch, Pouget (2016) - ** This paper derives the optimal

440   strategy for decisions in which the decision-maker is rewarded by the

441   value of the option chosen. Interestingly, the optimal strategy is

442   equivalent to a process of integrating differences in evidence streams, but

443   with decision boundaries that collapse over time. Relating this optimal

444   strategy to behavioural observations and to models of collective decision-

445   making ($=1=[13]) should prove valuable.

446 ¥ O'Donnell, Bulova, DeLeon, Khodak, Miller, Sulger (2015) - ** In this paper

447   the authors study a distributed cognition hypothesis, building on social

448   communication instead of individual cognition. One prediction of this

449   model is that brain investment in social species is reduced. The authors

450   present data from observations in wasps, which support the distributed

451   cognition hypothesis. They conclude that evolution of eusociality in wasps

452   was accompanied by the reduction of central processing brain areas,

453   which might be a significant feature of other types of social insects, too.

454 ¥ Frohnweiser, Murray, Pike and Wilkinson (2016) - * In this review the

455   authors survey the use of robots for understanding animal cognition,

456   including examples mentioned above. The authors argue that robotics

457   could have an important impact on understanding of perception, spatial

458   cognition, social cognition, and early cognitive development. Their

459   highlighting of social interactions, such as between fish and honeybees, is

460   particularly relevant to the study of collective decision-making.