Synchrony in Social Groups and Its Benefits

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Introduction

Self-organized synchrony is a group behavior which commonly occurs in nature. For example, groups of insects (Sullivan 1981), birds (Emlen 1952), and fish (Shaw 1978) can coordinate their moves and speeds with their neighbors so that they can all move together, behavior called swarming, flocking, schooling, and herding, for different kinds of species. Other examples of such behavior include fireflies that flash in unison (Mirollo and Strogatz 1990), pacemaker cells in the heart (Kuramoto and Yamagishi 1990), neural activities in cognitive processing (Fries 2005), etc. Synchrony is also a staple in social settings: choir singing (Müller and Lindenberger 2011), synchronization of applause in concert goers (Neda et al. 2000), and the formation of public opinion (Haken 2004) are easily recognizable examples. Another example is the collaboration in decentralized communities, e.g. among developers in Open Source Software (OSS) projects (Pinzger and Gall 2010; Xuan et al. 2012; Posnett et al. 2013). Yet other examples include the herd behavior among stock market traders (Scharfstein and Stein 1990; Chiang and Zheng 2010), the collective attention and emotion waves in online communities (Lehmann et al. 2012; Schweitzer and Garcia 2010), and language mimic (Gonzales et al. 2010).

It may be surprising that such synchronized behavior arises spontaneously without overall coordination and centralized authority. In fact, in all those groups synchronization emerges spontaneously, driven by simple decisions made by individuals in

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the group, based on limited sensory input of the behavior of their immediate neighbors. Staying synchronized with others takes effort, and thus comes at some cost to the individual. Thus, there are benefits to being synchronized, ranging from higher attractiveness to mates (fireflies) and evading predators (school of fish), to expressing forceful appreciation (concert goers).

Understanding the emergent behavior of complex systems which lack centralized governance would greatly enhance our understanding and interaction with the world around us. Recently, computer scientists have much benefited from observing self-organized biological systems and simulating their distributed rules in order to solve computational problems efficiently. E.g., a number of artificial intelligent algorithms (Navlakha and Bar-Joseph 2011; Anthony and Bartlett 2009; Dorigo and Blum 2005; Poli et al. 2007) were proposed to solve computational tasks of non-trivial difficulty (Vellido et al. 1999; Singh et al. 2009; Merkle et al. 2002; Aghdam et al. 2009; Gaing 2003). Meanwhile, these natural rules were also adopted to design distributed control schemes (Blaabjerg et al. 2006; Yu et al. 2012; Yan and Chen 2013) for groups of artifacts in order to deal with complex tasks, e.g., formation of spacecrafts (Beard and Hadaegh 2001) and robotic drumming (Crick et al. 2006). Effective study of synchrony in nature and society requires the use of quantitative analysis methods and data sets exemplifying such behavior.

Here we review work on social synchrony, a phenomenon arising when a group of people perform similar actions in a short period of time, actions which, over time, lead to the accomplishment of tasks of significant complexity (Choudhury et al. 2009). Although not all naturally occurring social synchrony is well understood, a significant corpus of work on these questions has amassed. A typical property of social synchrony is that individuals can obtain some information of others' behavior, followed by a simple modification of one's own behavior. Repeating this behavior leads to the emergence of the self-organized collective. This leads to several important questions that we and others have asked:

1. Synchrony is easy to describe and observe, but how can synchrony be measured and modeled in social groups?
2. If social ties among individuals and their behavior are in correlation, then what is the role of the social network structure on their synchronization?
3. Why do individuals synchronize their activities with each other, i.e., what is the benefit of synchronization? Does it lead to synergy?

This review chapter is structured around the above questions, and thus will elaborate on the quantitative aspects of social synchrony modeling, including specific metrics and models, the impact of social structure on the ability to synchronize, and the possible benefits of synchronization for the individual and community. Formal mathematical descriptions are used in the following sections for completeness; the chapter can be followed and understood sans the mathematical formalism.

Where appropriate, we will also summarize our results on the subject. Our own research work has recently centered on understanding self-organization in those social networks formed to achieve specific tasks, which we call task-oriented networks. To that end, we have focused significant attention on Open Source Software communities.

An established avenue for creating social capital, and reachly rewarding for the volunteer participants, OSS are examples of projects where people work in the absence of a coordinating hierarchy, to create snippets of code which when put together become complex artifacts of useful software. Some popular OSSs are Apache web server, Linux operating system, and the Mozzila web browser, but thousands of others exist. The software developers in OSS can be thought of as collaborating remotely on programming tasks, code integration, documentation writing, bug fixing, etc., while coordinating their work via electronic communication or by sharing examples. At the end of the chapter we present a case study on synchronization of software developers' activities in the Apache web server project.

Metrics and Models for Social Synchrony

Information exchange is necessary to achieve synchrony. A social network describes the links through which pairs of individuals exchange information. The following model is often used to describe the dynamics in social networks (Yan and Chen 2013; Park et al. 2006; Arenas et al. 2008; Gómez-Gardeñes et al. 2007):

$$\dot{x}_i(t) = F(x_i(t)) + \delta \sum_{j \in \pi_i} G(x_i(t), x_j(t)), i = 1, 2, \ldots, N \tag{1}$$

where $x_i(t)$ and π_i are the state and the neighbor set of individual v_i, δ is the coupling strength, $F(\cdot)$ is the individual dynamics, and $G(\cdot)$ is the coupling function through which different individuals interact with each other. The group of individuals $v_1, v_2, \ldots, v_N$ are considered mathematically synchronized if and only if

$$\sum_{i,j=1}^{N} x_i(t) - x_j(t) \to 0, \tag{2}$$

as $t \to \infty$ (Yu et al. 2012; Lü and Chen 2005; Li et al. 2007). However, Eq. (2) cannot be directly used to measure the synchrony in real systems because of their finite life span, and also because individuals may not take actions at the exactly same time, i.e., there might be short delays between their actions. To overcome these limitations, recently, several quantitative methods were proposed to measure social synchrony more realistically.

Sun et al. (2011) modeled synchrony in a group of cows, of two different behavioral states, eating or lying down. If we denote by $\tau_i(k)$ the kth time at which cow v_i switches to certain state (switching action), then the synchrony of this state between cows v_i and v_j is measured by

$$\Delta_{ij} = \frac{1}{K} \sum_{k=1}^{K} |\tau_i(k) - \tau_j(k)|, \tag{3}$$

where it is assumed that the two cows have the same number of switching actions. A smaller value of Δ_{ij} indicates more synchrony of the two individuals. Then, for

N cows, the group synchrony is measured by averaging over all pairwise synchronies:

$$\Delta = \langle \Delta_{ij} \rangle = \frac{1}{N^2} \sum_{i,j=1}^{N} |\Delta_{ij}|. \tag{4}$$

An alternative metric for synchrony is to directly count how often all individuals have the same state (Fæevik et al. 2008).

In many real cases different individuals may be active at very different rates in any given time interval, and each action may last for only a very short period of time, or even be discrete, i.e., the activities may form a Zero-measure set on the time axis. For example, in Open Source Software projects, different software developers have different rhythms of submitting changes to the software, and only the times when they submitted the changes are recorded. To address this situation, we have proposed the following more general metric for synchrony.

1. *Identify activity bursts.* From the time-series of activities for each individual, identify activity bursts based on a one-dimensional clustering method, i.e., first inter-activity time intervals larger than a predefined time window θ are obtained, then the activities between two consecutive large intervals are grouped as an "active burst", with occurrence time equal to the average of the times of the first and the last activities in this burst.
2. *Smooth bursts.* Let Γ_i be the set of all occurrence times of activity bursts of individual v_i. The smoothing function of the activity bursts is constructed by using Gaussian kernels (Moon 2001), as follows:

$$\varphi_i(t) = \frac{1}{|\Gamma_i|} \sum_{\xi \in \Gamma_i} \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(t-\xi)^2}{2\sigma^2}}. \tag{5}$$

3. *Calculate synchrony through correlation.* For each pair of individuals v_i and v_j, their centralized curves are obtained by subtracting the corresponding average value in the time interval $[T_L, T_U]$, where T_L and T_U are the minimum and maximum elements in the set $\Gamma_i \cup \Gamma_j$, respectively. Their synchrony is calculated by the Pearson correlation coefficient (Chatterjee and Price 1991) between the two centralized curves. Similarly, the group synchrony is calculated by averaging over all pairwise synchronies.

The metrics above calculate synchronies but don't tell us if those values are significantly different than those that would result from chance synchronization. To calculate the significance of the results we need a random or null model of behavior for all possible activities. One null model example is the uniform model, and another is a class of models that results from randomly permuting the labels on the events in the time series (bootstrapping) (Xuan et al. 2012). Using such models, the data can be randomized many times, each resulting in a population, and then pairwise synchronies can be computed for the individuals in each population. This procedure will yield a distribution with which the statistical significance of the real case can be assessed, using tests such as the t-test or the Wilcoxon-Mann-Whitney test.

The Impact of the Network Architecture on Synchrony

Based on the mathematical model represented by Eq. (1), we can see that synchrony may depend on the underlying network structure. As a result, it is of much scientific interest to characterize the kinds of networks which can facilitate synchrony.

In many theoretical works (Park et al. 2006; Arenas et al. 2008; Barahona and Pecora 2002; Hong et al. 2004; Motter et al 2005; Lerman and Ghosh 2012), it is simply assumed that

$$G(x_i(t), x_j(t)) = H(x_j(t)) - H(x_i(t)), \tag{6}$$

where $H(\cdot)$ is called the output function. Equation (6) is intuitive by considering that each individual is cooperative and hopes to be in an activity state close to those of its neighbors. By substituting Eq. (6) into Eq. (1), we have

$$\dot{x}_i(t) = F(x_i(t)) - \delta \sum_{j=1}^{N} L_{ij} H(x_j(t)), i = 1, 2, \ldots, N, \tag{7}$$

where L is the Laplacian matrix with its element $L_{ij} = -1$ if v_i and v_j are neighbors in the network, $L_{ii} = k_i$ if v_i has degree k_i, and $L_{ij} = 0$ otherwise. If the network is connected, i.e., there is a path between each pair of nodes, the Laplacian matrix has the eigenvalues satisfying $0 = \lambda_1 < \lambda_2 \le \lambda_3 \le \ldots \le \lambda_N$.

Nishikawa et al. (2003) found that the network's ability to synchronize is determined by λ_N/λ_2: the smaller that ratio, the less difficult it is to synchronize the dynamics of the nodes, and vice versa. Then, the question is which kind of networks have relatively small ratio of λ_N over λ_2. Several studies (Barahona and Pecora 2002; Donetti et al. 2003; Xuan et al. 2009) proved that the ratio is mainly determined by two factors: *small world* property and *homogeneity*. That is, a group of individuals are more likely to synchronize with each other when they are close to each other, i.e., have short average distance, and meanwhile have similar social status, i.e., have similar degrees. Thus, it is easy to infer that the fully connected network has the maximum synchronization ability since it has the minimum average distance and all the nodes have exactly the same degree. In fact, it can be proved that, in a fully connected network of N nodes, λ_2 and λ_N have the same value N, so that the ratio λ_N/λ_2 is equal to 1, which is the minimum over all connected networks (Chen et al. 2012). However, in most real cases, an individual cannot establish and keep the social ties with all others in a social system, especially when the system is large. Therefore, it is of much interest to identify the optimal network structures for synchrony under the condition that the average degree is fixed and much smaller than the network size. Donetti et al. (2003) proposed a method to minimize the eigenvalue ratio by a rewiring process, and they found that the optimal networks have extremely homogeneous structure, i.e., very small variance in degree, node distance, betweenness, and loop distributions (Costa et al. 2007), properties similar to those of *Cage* graphs (http://mathworld.wolfram.com/CageGraph.html) studied by many mathematicians. We obtained the same result by adopting another method (Xuan et al. 2009), where the average shortest path length rather than the ratio is minimized by a rewiring process under the condition that all nodes have exactly the same degree. In fact, we found that the average shortest path length and the ratio λ_N/λ_2 are linearly correlated in the optimization process. Since such optimization algorithms are always very time-consuming, we also proposed a growth model to obtain sub-optimal structure of large-scale networks in this work.

Most real-world networks have heterogeneous and modular structure (Barabási and Albert 1999; Girvan and Newman 2002; Ravasz et al. 2002; Xuan et al. 2006). When looking inside, it was found that hub nodes and the links connecting different modules play key roles in the synchronization process (Choudhury et al. 2009; Park et al. 2006; Wang and Chen 2002). For example, theoretical analysis (Wang and Chen 2002) proved that the network of individuals are more likely to be synchronized when those highly connected individuals are selected as leaders (they are not influenced by others), i.e., smaller number of leaders are needed, as compared to the random case, while empirical studies of the popular social site *Digg* (Choudhury et al. 2009) also indicate that large-scale social synchronies are more likely to arise if initialized by individuals with larger numbers of connections. Recent studies of synchrony on modular networks can also provide some useful insights. In fact, synchrony always occurs within each module at group level because the nodes in each module are always highly connected, almost like a fully connected subnetwork. However, the steady states of different modules may be independent from each other, i.e., the global synchrony cannot be achieved at system level, unless there are enough between-module links including some random and long-range links among these modules (Park et al. 2006; Oh et al. 2005; Zhou et al. 2007). These findings indicate that the links connecting different modules are important for the systemic behaviors.

The Kuramoto model (Arenas et al. 2008; Acebrón et al. 2005) may be the most well-known model to study the synchronization on networks. In this model, $F(\theta_i)\equiv\omega_i$ and $G(\theta_i,\theta_j)\equiv\sin(\theta_j-\theta_i)$, where ω_i is the natural frequency of node v_i, θ_i rather than x_i is adopted as the state of a node in order to keep these symbols the same as those in the related references, and the time t is omitted for simplicity. Then, we have the following collective dynamics:

$$\dot{\theta}_i = \omega_i + \delta \sum_{j\in\pi_i} \sin(\theta_j - \theta_i), i = 1,2,\ldots,N. \tag{8}$$

The synchronization here means that a group of individuals with different natural frequencies may oscillate with the same mean frequency when their coupling strength exceeds some critical point determined by the network structure. Note that this model can be theoretical analyzed, and Arenas et al. (2008) have provided a detailed review for this kind of study, which will not be extendedly discussed here. In fact, the Kuramoto model on networks has a simple linear form:

$$\dot{\theta}_i = \omega_i + \delta \sum_{j=1}^{N} L_{ij}\theta_j(t), i = 1,2,\ldots,N. \tag{9}$$

Recently, Lerman and Ghosh (2012) proposed a more general linear model by replacing the Laplacian matrix L in Eq. (9) by $R\equiv\alpha\, I-A$ in order to describe non-conservative social and biological processes more appropriately. The synchronization process partly depends on network structure, as a result, it can also be used to identify the network structure (Arenas et al. 2006; Boccaletti et al. 2007; Li et al. 2008; Fortunato 2010), e.g., detect communities. Interestingly, Lerman and Ghosh (2012) found that the identified network structure may be different by using different kinds of interactions in the synchronization scheme, which suggests that such methods for identifying local structures in complex networks must be used with great care.

Benefits of Social Synchrony: Toward Synergy

One of the reasons that a group of individuals prefer to take similar actions in certain time is that they want to deal with complex tasks more efficiently, in other words, they see synchrony as a way for the group to gain more than what each individual puts in. Thus, they aim to achieve *s*ynergy, defined as the creation of a whole that is greater than the sum of its parts (French et al. 2008). There are a dozen of such examples in nature. Ants are more likely to follow others in the same colony in order to perform better when they search and carry food as a group (Deneubourg et al. 1983; Dorigo et al. 1996). Male fireflies synchronize their flashing rhythm in order attract more females in a wide-range area (Otte 1980; Lewis and Cratsley 2008). A larger flocking of birds can help them detect approaching predators with a higher probability (Siegfried and Underhill 1975), meanwhile, formation flight can also reduce the flying cost on aerodynamics aspect (Hummel 1983), which can explain why groups of birds always present special shapes when they migrate over a long distance.

There are also many reasons for humans to synchronize our actions with others: Macrae et al. (2008) found that the synchrony of movements during social exchanges may facilitate the person perception process, e.g., the memory for an interaction partner's characters can be enhanced during this process. Hove and Risen designed experiments to show that interpersonal synchrony increases affiliation with a group (Hove and Risen 2009), similar to the effect of mimicry (Lakin et al. 2003), which may provide evidence for the hypothesis that such phenomena may play important role in social cohesion (Freeman 2000). While recently Paladino et al. (2010) suggested that synchrony may also have a magic to blurs self-other boundaries. All of these psychological findings indicate that social synchrony is selected evolutionarily, which may help a group of people increase their cooperative ability to better solve complex social tasks, as validated by Gonzales et al. (2010), Valdesolo et al. (2010), and Wiltermuth and Heath (2009) in their empirical studies. Moreover, Woolley et al. (2010) suggested that such cooperative ability can be characterized as a general collective intelligence factor, i.e., they found that the group performances on different tasks are significantly positively correlated, while the average and maximum performances of individual group members are not, and this factor can further be used to predict the group performance on other tasks. More on *collective intelligence* can be found in Woolley and Hashmi's chapter of this book. Having chosen a metric and model of synchrony as described in the above sections, synergy can be studied as an outcome, by modeling it in terms of the observed synchronizations in the groups or in the whole system. Great attention must be paid to following good modeling habits to avoid colinearities and other statistical obstacles.

A Case Study of Synchrony in Open Source Software Systems

Open Source Software systems provide a good platform to analytically study social synchrony and synergy among people. In OSS, groups of volunteer software developers create a software artifact by sharing programming experiences, finding bugs, or committing to files directly. OSS resemble ecological systems (Posnett et al. 2013) in that in addition to the actual developers, they attract thousands of users and other contributors looking to gain knowledge. These human resources, in turn, make the software grow faster and become better by providing feedbacks and joining the ranks of developers occasionally. Pavlic and Pratt, in another chapter of this book, compare eusocial insect behavior with human behavior conceptually in the context of OSS on a variety of dimensions.

Here, we look at projects from the Apache Software Foundation, and show how to validate whether developers prefer to work together or not, i.e., we show how to measure social synchrony and demonstrate that it is prevalent in these projects. We selected the six projects *Ant*, *Axis2_java*, *Cxf*, *Derby*, *Lucene*, and *Openejb* because they contain most developers so that we can get most meaningful statistical results. The data, gathered on March 24th, 2012, contains both the commit-code-to-file (commits) activities and the communication activities (emails) among developers. For each commit in a project, we have gathered the developer ID, file ID, the submitting time in seconds, and the numbers of added and deleted lines of code in each file. For each email communication activity, we have the sender ID, receiver ID, and the sending time in seconds.

Based on this data we calculated group synchrony. First, we filtered the data by selecting the files committed to by at least ten developers, and considered each month from the first to the last commit time as a time window. For each file f_i, out of a total of M across all six projects, we counted the number of developers, denoted by $n_i(t)$, that committed to this file in each time window t. Let X_i the total number of months in the time interval and $Y_i = \max_t n_i(t)$. Then, for each f_i, we obtained an $X_i \times Y_i$ binary count matrix A_i, with its elements $A_i(t, n_i(t)) = 1$ and the others equal to zero.

Note that the count matrix A_i shows that developers worked together in the same month on the same file, which, however, may be largely dependent on their own working rhythms, i.e., Y_i will be very large if the developers worked on the file frequently and will be very small otherwise. Therefore, to establish a baseline, we need to create simulated count matrices for comparison. To do that, we randomized the data as follows. If developer v_j committed to the file in h_{ij} months, we randomly permuted these h_{ij} active months among the total Y_i months. We repeated that process 100 times and got 100 binary matrices, denoted by $B_i^l, l = 1, 2, \ldots, 100$, for these random cases. Note that the real and simulated matrices may have different sizes, in

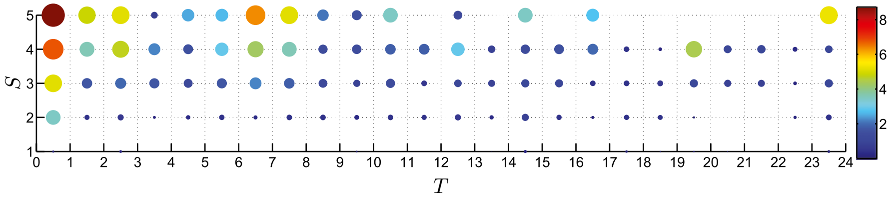

Fig. 1 The visualization of the significance matrix C. Here, S is the group size and T is a month in the first 2 years for each file since it was created. The elements with $a_{ij}<5$, $b_{ij}<0.1$, or $c_{ij}\leq 0$ are not shown. The point size is proportional to the value of the corresponding element in matrix C

which case we then expand the smaller matrices by filling them with zeros, so that all these matrices have the exactly same size. When considering all M files together, we also expand smaller matrices by the same method, and still denote them by A_i and B_i^l, $i = 1,2,\ldots,M, l = 1,2,\ldots,100$. Then, we can calculate the real and simulated matrix counts by:

$$A = \sum_{i=1}^{M} A_i, \quad B = \frac{1}{100}\sum_{i=1}^{M}\sum_{l=1}^{100} B_i^l \tag{10}$$

respectively. Based on these two matrices, we can get a significance matrix C with each element calculated by $c_{ij} = (a_{ij} - b_{ij})/b_{ij}$, which shows how significantly differently than chance the developers prefer to work together as a group at a certain scale. Here, only the elements satisfying $a_{ij}\geq 5$ and $b_{ij}\geq 0.1$ are considered. The significance matrix C for the first 2 years of the lives of the files is visualized in Fig. 1, where we can see that developers indeed prefer to work together as a group at larger scale, and the absence of most points when $S = 1$ indicates that they seldom work alone.

Conclusions

In this chapter, we have described social synchrony, and reviewed proposed metrics and models for it. We also discussed its possible benefits in social groups, especially how it leads to synergy among participants. We applied those methods to the analysis of distributed software development as a case study. In our analysis, we successfully discovered group synchrony of code developers when they commit to files, demonstrating the utility of this technique.

Future work involves extending this technique to identify synchrony patterns in OSS systems, based on which more realistic synchrony models for code developers can be created. These methods can also be used to analyze other social communities, where people cooperate with each other to finish complex tasks, e.g., online knowledge communities like Wikipedia, or question and answer communities such as Stack Overflow, where people share knowledge by shaping answers for technical problems together.

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References

Acebrón JA, Bonilla LL, Vicente CJP, Ritort F, Spigler R (2005) The Kuramoto model: a simple paradigm for synchronization phenomena. Rev Mod Phys 77(1):137–185

Aghdam MH, Ghasem-Aghaee N, Basiri ME (2009) Text feature selection using ant colony optimization. Expert Syst Appl 36(3):6843–6853

Anthony M, Bartlett PL (2009) Neural network learning: theoretical foundations. Cambridge University Press, Cambridge

Arenas A, Díaz-Guilera A, Pérez-Vicente CJ (2006) Synchronization reveals topological scales in complex networks. Phys Rev Lett 96(11):114102

Arenas A, Díaz-Guilera A, Kurths J, Moreno Y, Zhou C (2008) Synchronization in complex networks. Phys Rep 469(3):93–153

Barabási A-L, Albert R (1999) Emergence of scaling in random networks. Science 286(5439):509–512

Barahona M, Pecora LM (2002) Synchronization in small-world systems. Phys Rev Lett 89(5):054101

Beard RW, Hadaegh FY (2001) A Coordination architecture for spacecraft formation control. IEEE Trans Control Syst Technol 9(6):777–790

Blaabjerg F, Teodorescu RE, Liserre M, Timbus AV (2006) Overview of control and grid synchronization for distributed power generation systems. IEEE Trans Ind Electron 53(5):1398–1409

Boccaletti S, Ivanchenko M, Latora V, Pluchino A, Rapisarda A (2007) Detecting complex network modularity by dynamical clustering. Phys Rev E 75(4):045102(R)

Chatterjee S, Price B (1991) Regression analysis by example. Wiley, New York

Chen J, Lu J-A, Zhan C, Chen G (2012) Laplacian spectra and synchronization processes on complex networks. In: Thai MT, Pardalos PM (eds) Handbook of optimization in complex networks: theory and applications. Springer, Heidelberg, pp 81–113

Chiang TC, Zheng D (2010) An empirical analysis of herd behavior in global stock markets. J Bank Financ 34(8):1911–1921

Choudhury MD, Sundaram H, John A, Seligmann DD (2009) Social synchrony predicting mimicry of user actions in online social media. In: The proceedings of the 2009 international conference on computational science and engineering, Vancouver, Canada, pp 151–158

Costa LF, Rodrigues FA, Travieso G, Boas PRV (2007) Characterization of complex networks: a survey of measurements. Adv Phys 56(1):167–242

Crick C, Munz M, Scassellati B (2006) Synchronization in social tasks: robotic drumming. In: The proceedings of the 15th IEEE international symposium on robot and human interactive communication, Hatfiled, UK, pp 97–102

Deneubourg JL, Pasteels JM, Verhaeghe JC (1983) Probabilistic behaviour in ants: a strategy of errors? J Theor Biol 105(2):259–271

Donetti L, Hurtado PI, Muñoz MA (2003) Entangled networks, synchronization, and optimal network topology. Phys Rev Lett 95(18):188701

Dorigo M, Blum C (2005) Ant colony optimization theory: a survey. Theor Comput Sci 344:243–278

Dorigo M, Maniezzo V, Colorni A (1996) Ant system: optimization by a colony of cooperating agents. IEEE Trans Syst Man Cybern Part B: Cybern 26(1):29–41

Emlen JJT (1952) Flocking behavior in birds. The Auk 69(2):160–170

Fæevik G, Tjentland K, Løvik S, Andersen IL, Bøe KE (2008) Resting pattern and social behaviour of dairy calves housed in pens with different sized lying areas. Appl Anim Behav Sci 114:54–64

Fortunato S (2010) Community detection in graphs. Phys Rep 486(3–5):75–174
Freeman W (2000) A neurobiological role of music in social bonding. In: Wallin NL, Merker B, Brown S (eds) The origins of music. MIT, Cambridge, pp 411–424
French R, Schermerhorn JR, Rayner C, Rees G, Rumbles S, Hunt JG, Osborn RN (2008) Organizational behaviour. Wiley, New York
Fries P (2005) A mechanism for cognitive dynamics: neuronal communication through neuronal coherence. TRENDS Cogn Sci 9(10):474–480
Gaing Z-L (2003) Particle swarm optimization to solving the economic dispatch considering the generator constraints. IEEE Trans Power Syst 18(3):1187–1195
Girvan M, Newman MEJ (2002) Community structure in social and biological networks. Proc Natl Acad Sci USA 99(12):7821–7826
Gómez-Gardeñes J, Moreno Y, Arenas A (2007) Paths to synchronization on complex networks. Phys Rev Lett 98(3):034101
Gonzales AL, Hancock JT, Pennebaker JW (2010) Language style matching as a predictor of social dynamics in small groups. Commun Res 37(1):3–19
Haken H (2004) Synergetics: introduction and advanced topics. Springer, Heidelberg
Hong H, Kim BJ, Choi MY, Park H (2004) Factors that predict better synchronizability on complex networks. Phys Rev E 69(6):067105
Hove MJ, Risen JL (2009) It's all in the timing: interpersonal synchrony increases affiliation. Soc Cogn 27:949–960
http://mathworld.wolfram.com/CageGraph.html
Hummel D (1983) Aerodynamic aspects of formation flight in birds. J Theor Biol 104(3):321–347
Kuramoto T, Yamagishi H (1990) Physiological anatomy, burst formation, and burst frequency of the cardiac ganglion of crustaceans. Physiol Zool 63(1):102–116
Lakin JL, Jefferis VE, Cheng CM, Chartrand TL (2003) The chameleon effect as social glue: evidence for the evolutionary significance of nonconscious mimicry. J Nonverbal Behav 27:145–162
Lehmann J, Gonçalves B, Ramasco JJ, Cattuto C (2012) Dynamical classes of collective attention in Twitter. In: The proceedings of the 2012 international world wide web conference committee, Lyon, pp 251–260
Lerman K, Ghosh R (2012) Network structure, topology, and dynamics in generalized models of synchronization. Phys Rev E 86(2):026108
Lewis SM, Cratsley CK (2008) Flash signal evolution, mate choice, and predation in fireflies. Annu Rev Entomol 53:293–321
Li C, Sun W, Kurths J (2007) Synchronization between two coupled complex networks. Phys Rev E 76(4):046204
Li D, Leyva I, Almendral JA, Sendiña-Nadal I, Buldú JM, Havlin S, Boccaletti S (2008) Synchronization interfaces and overlapping communities in complex networks. Phys Rev Lett 101(16):168701
Lü J, Chen G (2005) A time-varying complex dynamical network model and its controlled synchronization criteria. IEEE Trans Autom Control 50(6):841–846
Macrae CN, Duffy OK, Miles LK, Lawrence J (2008) A case of hand waving: action synchrony and person perception. Cognition 109:152–156
Merkle D, Middendorf M, Schmeck H (2002) Ant colony optimization for resource-constrained project scheduling. IEEE Trans Evol Comput 6(4):333–346
Mirollo RE, Strogatz SH (1990) Synchronization of pulse-coupled biological oscillators. SIAM J Appl Math 50(6):1645–1662
Moon BS (2001) A gaussian smoothing algorithm to generate trend curves. Korean J Comput Appl Math 8(3):507–518
Motter AE, Zhou C, Kurths J (2005) Network synchronization, diffusion, and the paradox of heterogeneity. Phys Rev E 71(1):016116
Müller V, Lindenberger U (2011) Cardiac and respiratory patterns synchronize between persons during choir singing. PLoS One 6(9):e24893
Navlakha S, Bar-Joseph Z (2011) Algorithms in nature: the convergence of systems biology and computational thinking. Mol Syst Biol. doi:10.1038/msb.2011.78

Neda Z et al (2000) Self-organizing processes: the sound of many hands clapping. Nature 403:849–850
Nishikawa T, Motter AE, Lai Y-C, Hoppensteadt FC (2003) Heterogeneity in oscillator networks: are smaller worlds easier to synchronize? Phys Rev Lett 91(1):014101
Otte D (1980) On theories of flash synchronization in fireflies. Am Nat 116(4):587–590
Oh E, Rho K, Hong H, Kahng B (2005) Modular synchronization in complex networks. Phys Rev E 72(4):047101
Paladino MP, Mazzurega M, Pavani F, Schubert TW (2010) Synchronous multisensory stimulation blurs self-other boundaries. Psychol Sci 21:1202–1207
Park K, Lai Y-C, Gupte S (2006) Synchronization in complex networks with a modular structure. Chaos 16(1):015105
Pinzger M, Gall HC (2010) Dynamic analysis of communication and collaboration in OSS projects. In: Collaborative software engineering. Springer, Heidelberg, pp 265–284
Poli R, Kennedy J, Blackwell T (2007) Particle swarm optimization. Swarm Intell 1(1):33–57
Posnett D, D'Souza R, Devanbu P, Filkov V (2013) Dual ecological measures of focus for software development. In: The proceedings of the 2013 international conference of software engineering, San Francisco
Ravasz E, Somera AL, Mongru DA, Oltvai ZN, Barabási A-L (2002) Hierarchical organization of modularity in metabolic networks. Science 297(5586):1551–1555
Scharfstein DS, Stein JC (1990) Herd behavior and investment. Am Econ Rev 80(3):465–479
Schweitzer F, Garcia D (2010) An agent-based model of collective emotions in online communities. Eur Phys J B 77(4):533–545
Shaw E (1978) Schooling fishes: the school, a truly egalitarian form of organization in which all members of the group are alike in influence, offers substantial benefits to its participants. Am Sci 66(2):166–175
Siegfried WR, Underhill LG (1975) Flocking as an anti-predator strategy in doves. Anim Behav 23:504–508
Singh KP, Basant A, Malik A, Jain G (2009) Artificial neural network modeling of the river water quality-a case study. Ecol Model 220(6):888–895
Sullivan RT (1981) Insect swarming and mating. Fla Entomol 64(1):44–65
Sun J, Bollt EM, Porter MA, Dawkins MS (2011) A mathematical model for the dynamics and synchronization of cows. Phys D: Nonlinear Phenom 240(19):1497–1509
Valdesolo P, Ouyang J, DeSteno D (2010) The rhythm of joint action: synchrony promotes cooperative ability. J Exp Soc Psychol 46(4):693–695
Vellido A, Lisboa PJG, Vaughan J (1999) Neural networks in business: a survey of applications. Expert Syst Appl 17:51–70
Wang XF, Chen G (2002) Pinning control of scale-free dynamical networks. Phys A: Stat Mech Appl 310(3–4):521–531
Wiltermuth SS, Heath C (2009) Synchrony and cooperation. Psychol Sci 20:1–5
Woolley AW, Chabris CF, Pentland A, Hashmi N, Malone TW (2010) Evidence for a collective intelligence factor in the performance of human groups. Science 330(6004):686–688
Xuan Q, Li Y, Wu T-J (2006) Growth model for complex networks with hierarchical and modular structures. Phys Rev E 73(3):036105
Xuan Q, Li Y, Wu T-J (2009) Optimal symmetric networks in terms of minimizing average shortest path length and their sub-optimal growth model. Phys A: Stat Mech Appl 388(7):1257–1267
Xuan Q, Gharehyazie M, Devanbu P, Filkov V (2012) Measuring the effect of social communications on individual working rhythms: a case study of open source software. In: The proceedings of 2012 ASE/IEEE international conference on social informatics, Washington, DC
Yan F, Chen G (2013) Distributed consensus and coordination control of networked multi-agent systems. In: Kocarev L (ed) Consensus and synchronization in complex networks. Springer, Heidelberg, pp 51–68
Yu W, DeLellis P, Chen G, Bernardo MD, Kurths J (2012) Distributed adaptive control of synchronization in complex networks. IEEE Trans Autom Control 57(8):2153–2158
Zhou T, Zhao M, Chen G, Yan G, Wang B-H (2007) Phase synchronization on scale-free networks with community structure. Phys Lett A 368(6):431–434