Optimal Observation for Cyber-physical Systems

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A Fisher-information-matrix-based Approach

Springer

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To our mentors and families

Preface

Cyber-physical systems (CPSs) are emerging as an integrative research field aimed towards a new generation of engineered systems. From a dynamic systems and control point of view, CPS can be defined in the following way: "computational thinking and integration of computation around the physical dynamic systems form CPSs where sensing, decision, actuation, computation, networking, and physical processes are mixed." CPS applications can be found in medical devices and systems, patient monitoring devices, automotive and air traffic control, advanced automotive systems, process control, environmental monitoring, avionics, instrumentation, oil refineries, water usage control, cooperative robotics, manufacturing control, smart greener buildings, etc.

CPSs are mostly distributed parameter systems (DPSs) and dynamic evolutions happen not only along the time axis but also along spatial axes. Within the spatial domain of interest, due to the infinite-dimensional nature, it is natural and fundamental to consider the optimal observation or optimal measurement problems in CPSs.

Recently, wireless sensor networks (WSNs) have attracted many researchers from both industry and academia and it is widely believed that the technology will bring important changes to our society in this century. An important class of application for the WSN is to observe physical systems, where the sensor networks together with the physical processes are considered as part of CPSs. The research and development of WSNs incorporate knowledge from many disciplines, such as communications, computer engineering and computer science, electronic engineering and mathematics, to name a few.

The authors of this book come from both academia and industry and bring expertise from both sides. Overall, we intend to make this book practical since the authors were motivated by real engineering challenges. In the past 6 years, based on our award-winning hardware experiment systems, we have attempted to solve challenging problems and to generalize the results to address a large class of WSN design issues. Two hardware platforms have been described in this book. The MAS-net (mobile actuator and sensor networks) project won 2nd place on the 2005 Cross-bow's Smart Dust Challenge and was demonstrated on the TinyOS Technical Exchange at UC Berkeley. Our sensor selection testbed was demonstrated at the 2006

DSN Symposium (International Symposium on Innovations and Real Time Applications of Distributed Sensor Networks). Later, some preliminary results of our sensor selection method were presented at the 2007 IEEE Sarnoff Symposium at Princeton University and we won 3rd Best Paper Prize in the student paper/poster competition session. Some theoretical analysis results are presented in the book with clear practical motivations to address some important design questions. Therefore, this book is not intended to be a pure theoretical research monograph.

Based on our hands-on experiences, we think that the fundamental challenge in the area of WSN is to design and implement systems that are robust and reliable for real-world safety-critical applications. In practice, the design frequently involves delicate tradeoffs between precise estimates and physical system constraints. In addition, the disturbances should be quantitatively analyzed in order to ensure the quality of the sensor network service. Due to the complexity of the problems, it is usually very difficult to balance the tradeoffs by heuristic or ad hoc methods. For example, energy costs and estimation precision are counteractive under certain cases, in terms that putting too many sensors in the dormant mode may save precious on-board energy but also nullify the observation. In light of this challenge, this book presents a unified theoretical framework, which is based on the well-established theory of optimal experiment design (OED), to solve a large class of optimal observation problems involving WSNs. The Fisher information matrix (FIM), which has been studied for decades, plays a key role in the theoretical framework. We would like to demonstrate in this book that, the FIM framework is fundamental in solving a wide spectrum of design problems for WSNs in CPSs.

We addressed three major problems in the book.

The first addressed problem is the trajectory optimization for observation of DPSs, where wireless sensors were mounted on mobile robots. In this example, the cost function in the problem was constructed based on the FIM. The problem was formulated as an optimal control problem. It is demonstrated that FIM is applicable to mobile sensor networks for CPSs modeled by partial differential equations (PDEs).

The second problem is the optimal sensor selection problem (SSP) illustrated in a target tracking scenario. In this case, the positions of the sensors are fixed. Instead of driving the sensors along certain trajectories like the first problem, we activate or scan "just enough" sensors in order to save the precious on-board energy. Thanks to FIM, we proved that the observation based on a small number of sensors could be as precise as the observation based on the whole network. We proposed a convex optimal sensor selection (COSS) framework to select the proper sensors for generic parameters identification problems. We also discussed how to place sensors to ensure that the network is optimal sensor selection feasible.

Finally, we discussed the optimal beacon placement problem, where the balance between the positioning error and beacon placement is discussed. Since the positioning errors of many localization systems are affected by the placement of the beacon nodes, it is desirable to place the beacons properly, such that the maximum positioning error is minimized. To solve the problem, we formulate a semi-infinite programming (SIP) problem, where the cost function is again based on FIM.

In summary, the optimal observation problems of WSNs considered in this book share the same theoretical framework in terms of OED that are formulated as an optimization problem with a cost function in terms of FIM.

The topic of CPS is fantastic as well as challenging. Due to the multidisciplinary nature of the topic, we frequently come across problems that are out of our expertise. We are lucky that we can always gain valuable knowledge from our colleagues and friends. We are grateful to all the people helped us and supported our research. Some of them shared their valuable knowledge and experiences with us. Many of them spent their valuable time to review our work and provided faithful and insightful feedback.

First of all, we appreciate Dr. Kevin L. Moore of Colorado School of Mines for his invaluable contributions to the MAS-net project. He even served as a carpenter to make the wooden frame of the fog box of the MAS-net platform. He spent uncountable hours discussing the details with us and helped us to bring the idea into reality. Our sincere thanks go to Dr. Dariusz Uciński of the Institute of Control and Computation Engineering, University of Zielona Góra for constructive research collaborations over the years. His book on OED introduced us to this fantastic topic. We would like to thank Dr. Tamal Bose for his encouragement and support when we participated in the 2005 Smart Dust Challenge.

We are grateful to all the people who helped the MAS-net project, including Dr. Kevin L. Moore and the team members, Mr PengYu Chen, Mr ZhongMin Wang, Ms Anisha Arora, Mr HaiYang Chao and Mr William Burgeous; former CSOIS members, Dr. Lili Ma, Dr. JinSong Liang, Mr Dan Stormont, Mr Bharath Ramaswamy. We would also present our appreciation to friends and colleagues: Dr. XiaoChun Xu, Dr. Vehbi Cagri Gungor, Dr. Hyo-Sung Ahn, Dr. Mohsen Jafari and Dr. Stanislava Soro.

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Last but not least, we are grateful to Oliver Jackson, Editor, Springer UK, for his visionary management that made this book project possible. We also wish to thank Aislinn Bunning, Editorial Assistant, Springer UK for her great patience and help in the copy editing phase.

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Contents

Abbreviations and Notation

Abbreviations

ADC	analog-to-digital converter
AOA	angle of arrival
ASIC	application specific integrated circuit
CBR	chemical, biological, and/or radiological
CDMA	code division multiple access
COSS	convex optimal sensor selection
CPS	cyber-physical system
CRLB	Cramér–Rao lower bound
CSS	chirp spread spectrum
DPS	distributed parameter system
eCOSS	elimination-based convex optimal sensor selection
FIM	Fisher information matrix
FPGA	field programmable gate array
GPS	global positioning system
GUI	graphical user interface
hCOSS	heuristic convex optimal sensor selection
ICS	integrated control system
IEEE	Institute of Electrical and Electronic Engineers
LQI	link quality indicator
LS	least squares
MAP	maximum a posteriori
MAS-net	mobile actuator-sensor network
ML	maximum likelihood
OED	optimum experimental design
OWR	one-way ranging
PDE	partial differential equation
PDF	probability density function
PMF	probability mass function

POA	phase of arrival
RF	radio frequency
RFID	radio-frequency identification
RSSI	received signal strength indicator
RIOTS	recursive integration optimal trajectory solver
RTT	round-trip time
SIP	semi-infinite programming
SNR	signal-to-noise ratio
SSP	sensor selection problem
TOA	time of arrival
TDOA	time difference of arrival
TOF	time of flight
UAV	unmanned aerial vehicles
UWB	ultra-wideband
WLS	weighted least squares
WSN	wireless sensor network

Comments on Symbols

Fonts — Vectors are typed in bold math font, such as vector $\mathbf{v}$. Matrices are indicated by capital math font, e.g., M. Note that random variables are also denoted by capital font, e.g., X. Thus, $\mathbf{p} \neq p \neq P \neq \mathbf{p}$, since $\mathbf{p}$ is a vector, p is a scalar, and P is a matrix. By default, all vectors are column vectors. For example, $\mathbf{p} = \begin{pmatrix} p_1 \\ p_2 \\ \vdots \\ p_n \end{pmatrix} = \begin{pmatrix} \mathbf{p}_{(1)} \\ \mathbf{p}_{(2)} \\ \vdots \\ \mathbf{p}_{(n)} \end{pmatrix}$. Note that $\mathbf{p}_{(1)}$ is the first entry of the vector $\mathbf{p}$, and $\mathbf{p}_{(1)}$ is a scalar. $\mathbf{p}_1$ is a vector. By default, M and M_1 are two difference matrices, and $M \neq M_1$.

Subscripts — The subscripts in brackets indicate scalar entries of a matrix or vector. The subscripts without brackets are instances of variables. Capital subscripts are parts of the variable's name. So, t and t_A are different scalars. Lower case subscripts, e.g., i, j, k, are used as indices for positive integers. For example, $\mathbf{p}_{(i)}$ is the ith entry of the vector $\mathbf{p}$, and $\mathbf{p}_{(i)}$ is a scalar. Similarly, $M_{(i,j)}$ is the ith row and jth column scalar entry of matrix M. $M_{(i,:)}$ is the ith row vector of matrix M, and $M_{(:,i)}$ is the ith column vector of matrix M. $\mathbf{p}_i$ is the ith $\mathbf{p}$ vector, where $i = 1, 2, 3, \cdots$. Note that p_i is the ith p, and p_i is a scalar. Thus, $\mathbf{p}_i \neq p_i$. However, $\mathbf{p}_{(i)} = p_i$ by default, and both of them are scalars.

$\square$ — The sign $\square$ represents Q.E.D., which is the end of a proof.

$\diamond$	The sign $\diamond$ indicates the end of a remark or an example.

Notation in Chapter 2

m	The weight of one robot.
I	The inertia of the robot along the z axis. Note that I is a scalar.
l	The length of the robot's axis.
r	Wheel radius. The left and right wheels have the same radius.
α	The yaw angle as shown in Fig. 2.1.
(x, y)	The coordinate of the center of the axis. Note that $\mathbf{x}$ is not x.
τ_l,τ_r	The torque applied on the left and right wheel, respectively. $\tau = [\tau_l, \tau_r]^T$.
A, B, $\mathbf{x}$, τ	The parameters, states and the control signal for a single robot.
A_T, B_T, $\mathbf{x}_T$, τ_T	The parameters, states and the control signal for three robots.
b	The edge length of the robot's square chassis. It is assumed that the wheels and the axis are mounted on a square chassis.
$\chi(t)$	Mayer state.
$\chi_{\mathrm{dl}}(t)$	Stacks all the entries on the diagonal and below the diagonal of χ to a vector.
Ω	The domain for valid input variables.
$\partial\Omega$	The boundary of Ω.
n	Number of robots.
$\mathbf{c}$	The vector of unknown parameters. $\mathbf{c} = [c_1, c_2, c_3]^T$.

Notation in Chapter 3

n	The total number of sensors. Note that $n \neq \mathbf{n}$.
n_i or $\mathbf{n}_{(i)}$	The number of samples that sensor i collects in each t_S, the sampling period. Note that $\mathbf{n} = [n_1, n_2, \cdots]^T \neq n$.
P_r	Probability function.
m	The number of parameters for identification.
t_S	The total sampling time. In t_S, sensor i collects n_i samples.
n_S	The maximum total number of samples of the whole WSN in t_S time slot.
c_1, c_2, etc.	The coefficients in sensor models.
σ_i, $\bar{\sigma}_i$, $\tilde{\sigma}_i$	σ_i is the standard deviation of the noise of the ith sensor. $\bar{\sigma}_i$ is the standard deviation for the ith averaged sensor measurement. $\tilde{\sigma}_i$ is similar to $\bar{\sigma}_i$ but averaged over nominal sampling rates.
y_i or $\mathbf{y}_{(i)}$	The nominal value of sensor i. It is computed by the model of events.
v_i	The noise of sensor i.
s_i or $\mathbf{s}_{(i)}$	Real value of the reading of sensor i. $s_i[k] := y_i[k] + v_i[k]$.

$\bar{s}_i$	Averaged sensor i's reading.
$\mathcal{N}(\mu, \sigma)$	Gaussian (normal) distribution with the expectation of μ and variance of σ.
$\mathbf{p}$	Normalized sampling rate of sensor i. $\hat{\mathbf{p}}[k]$ is the optimized normalized sampling rate for the kth iteration.
$\mathbf{r}_i$	Position of sensor i. $\mathbf{r}_i$ is assumed precisely known. In addition $\mathbf{r}_i \neq \mathbf{r}_j$, for any $i \neq j$. By default, $\mathbf{r}_i$ is a 2D vector like $\begin{pmatrix} x_i \\ y_i \end{pmatrix}$.
$\mathbf{q}$, $\mathbf{q}^*$	$\mathbf{q}$ is the nominal position of the target. Specifically, $\mathbf{q}^*$ is the true position of the target.
$\mathbf{1}$	An all-one vector, i.e., $[1, 1, \cdots, 1]^T$.
∇	Gradient. For example, $\nabla_{\mathbf{q}}$ is the gradient with respect to $\mathbf{q}$.
$\mathbf{a} \geq b$	Each entry of vector $\mathbf{a}$ is no less than the scalar b. $a_i \geq b$; e.g., $\mathbf{p} \geq 0$.
$A \succeq B$	Matrix $A - B$ is positive semidefinite.

Notation in Chapter 4

Ω	The domain for deployed mobile node and beacons.
$\mathbf{q}_i$	The position of the ith beacon.
$\mathbf{p}_i$	The position of the ith mobile node.
m	Number of mobile nodes.
n	Number of beacons.

Chapter 1
Introduction

1.1 Motivation for the Book

1.1.1 Challenges of Observation for Cyber-physical Systems

This book covers several design issues on wireless sensor network (WSN) based physical quantity observation in cyber-physical systems (CPSs). In brief, we are interested in observing physical systems by massively deployed, small, embedded low-power and low-cost wireless sensor nodes, where microprocessors, sensors, power, communication unit and other peripherals are integrated on one board or even one chip. More specifically, we focus on how to utilize the physical laws, or models, to systematically design WSNs and enhance their performances under real-world scenarios.

CPS is emerging as an integrative research field aimed toward a new generation of engineered systems. From the dynamic systems and control point of view, CPS can be defined in the following way: "Computational thinking and integration of computation around the physical dynamic systems for CPS where sensing, decision, actuation, computation, networking and physical processes are mixed." CPS applications can be found in medical devices and systems, patient monitoring devices, automotive and air traffic control, advanced automotive systems, process control, environmental monitoring, avionics, instrumentation, oil refineries, water usage control, cooperative robotics, manufacturing control, smart greener buildings, etc.

CPSs are mostly distributed parameter systems (DPSs) and dynamic evolutions happen not only along the time axis but also along spatial axes. Within the spatial domain of interest, due to the infinite-dimensional nature, it is natural and fundamental to consider the optimal observation or optimal measurement problems in CPSs.

The topic of WSN has attracted much research attention lately and academia and industry are actively promoting the technology. Researchers from various backgrounds are incorporated into the WSN community and new promising applications are being reported regularly. Despite many intelligent proposals on prospective applications in the area, the technology has not yet been widely adopted by the industry. Many factors, such as lack of a "killer application," insufficient scalability, need of energy efficiency, etc., have been incriminated as the bottleneck of WSN adoption and many are working to improve these factors.

In this book, we attack the optimal observation problem from the aspect of system-level design methodology. We argue that in order to ensure the observation quality, the impact of each design factor on the observation error should be studied quantitatively. Because real-world WSNs usually incorporate analysis methods in multiple disciplines, we propose to use the Fisher information matrix (FIM) as the unifying framework for comprehensive optimal observation designs. We will apply the FIM to some interesting WSN design problems and compare the alternative approaches.

To understand the importance of the FIM, some background knowledge is helpful. For the system-level design, it is important to ensure the observation quality by precision and robustness criteria, which are described as follows.

- Precision. If the sensor network is used to observe a physical quantity, the estimated value should also be bounded by a confidence interval or region, such as 100 ± 0.1, in order to precisely describe the quality of the observation. Higher reliability requires more precise observation, i.e., smaller confidence intervals. If a state, such as normal state or exception state, is being observed by the sensor network, the estimation precision should be characterized by statistical errors, such as false positive and false negative probabilities.
- Robustness. The observation should be immune to disturbances, such as unrelated cell phone or WiFi signals.

Compared with precision, robustness is relatively loosely defined. In practice, we analyze robustness by studying the impact of each disturbance factor on the estimation precision.

Let us consider the following proposed WSN applications:

- Structural health monitoring [1]. Apply WSNs to monitor the mechanical structural integrity of buildings, bridges, and vehicles etc.
- Predictive maintenance [2,3]. Utilize WSNs to detect potential faults on expansive machines, such as the engine of a ship, and deliver alarms accordingly.
- Wildfire monitoring [4]. Detect and monitor wildfires in forests.
- Landslide prediction [5]. Forecast landslides, save lives and valuable assets.

There are more example applications in the following chapters. Obviously, these safety-critical applications have high demands on the reliability of the sensor networks. A faulty observation may result in loss of millions of dollars and even death. Therefore, they must be designed based on more systematic methods compared with many other wireless communication systems, such as WiFi or cell phone.

Let us take the structure monitoring application as an example. The typical method to check the structural health of a bridge is to close it and examine its components using human experts, which takes around one day per year. Even if the sensor network can observe accurately the status of the bridge, i.e., healthy or unhealthy, such that 99% of the time its prediction is correct, that means, roughly speaking, that the bridge may be closed three days a year due to false alarms from the sensor network, which is worse than the current approach. In addition, there are chances that the system cannot predict collapse when the event is really about to happen. Given the fact that wireless communication is intrinsically not reliable, this application is rather challenging. To guarantee industry-acceptable reliability and accuracy, we may have to study quantitatively the impact of every small factor, such as sensor placement errors or interferences from a cell phone user on the bridge, on the system observation error.

Notice that understanding the impacts of these factors on communication metrics, such as the throughput of the sensor network, is not enough, because the ultimate task is to monitor the status of the bridge, not to of construct a fast communication channel. The theory of observability indicates that a high performance communication module may not secure the design of the observer. If a physical state is unobservable, or cannot be observed accurately, it is not helpful to improve the communication channel alone. We will address the theory in the math background part of this chapter. For such cases, the solution is to find an alternative way to observe the physical system of interest, such as measuring different physical quantities.

The aforementioned applications and numerous other ideas all share the same characteristic: they may have significant positive impacts on society only if the observation qualities are high enough.

1.1.2 Lessons Learned from Experience

In the following, we explain our motivation based on our first-hand experiences.

We started the journey from our MAS-net project. Our proposed application is to monitor and eliminate diffusing pollutions using mobile wireless sensor nodes. Instead of considering the sensor network as a pure communication system, we take it as an observer that provides feedback signals to the controller of the application. Rather than pursuing the traditional metrics for communication systems, such as the throughput, we design and optimize the sensor network based on how much valuable information it provides to the specific pollution monitoring task. The project won 2nd place in 2005 Crossbow's Smart Dust Challenge and was demonstrated on TinyOS Technical Exchange at UC Berkeley. While working on the project, we came across many design problems. The difficulty usually came from questions like "in order to guarantee the error of certain value is within a certain bound, what is the acceptable interval or optimal value of another design factor?" For example, what is the optimal sampling rate of the network in order to assure the observation error is smaller than a threshold? How much positioning error on the sensor nodes can be tolerated? How much clock drift is acceptable? How many sensor nodes are required and how to drive them? Related problems have been more or less discussed in the literature, but they were attacked by various methods based on distinct theories, thus it is usually difficult to combine them into one framework. This raises many design issues and introduces difficulties on trouble shooting. For example, the positioning errors on the mobile sensor nodes depend on the resolution of the encoders on the sensors, the precisions of a head camera that locates each robotic sensor node based on the markers on their tops, and the network communication protocol, through which the base station, which is a PC, broadcasts calibration messages to mobile sensors for better positioning. In brief, we tried to design a protocol that can tolerate less precise encoders. Because the effort to find an off-the-shelf solution in the literature was in vain, we had to take the notorious trial-and-error approach. However, we finally had to use encoders with higher resolution in order to make the system reasonably stable. This problem was not the only one in the project.

After the platform development, we summarized the lessons that we learned from the development and we gain time for a literature review. The theory of FIM and information matrix[1] and the semigroup theory caught our attention. Both are capable of answering some puzzles in our mind. We preferred FIM since it is more practical for our engineering applications. We collaborated with Dr. Uciński and Dr. Liang on a paper to address the robotic sensor trajectory optimization issue using the FIM.

Later, we developed a hardware demonstration system called "sensor selection testbed" following the engineering disciplines. Equipped with the FIM, we can estimate the impacts of all the design factors on the observation error; trouble shooting was very systematic, and the hardware platform was quite stable.

As will be described in Chap. 3, the sensor selection testbed was designed to track a halogen lamp using 15 wireless sensor nodes equipped with light sensors. The design started from a couple of error analysis equations based on the FIM followed by some simulations on a PC. While working on the hardware, we first conducted several experiments to profile the characteristics of the light sensor. Second, after plugging in the sensor's characteristic curve into the simulation program, it is clear that a small, bright and nonflashing light source is required. Therefore a halogen lamp, rather than a fluorescent or incandescent lamp, was selected. More comparisons on halogen and fluorescent lamps are shown in Chap. 3. Third, the FIM analysis was also useful to identify sources of external disturbances. The effects of communication packet loss and ambient light were distinguished and compensated separately. Finally, the system was stable enough so that we could take it to Washington DC and demonstrate it at the 2006 DSN symposium (International Symposium on Innovations and Real Time Applications of Distributed Sensor Networks). Once the hardware is set up, we only need to measure the intensity of the ambient light, which takes less than a minute, and then the 15 sensors can collate to track the lamp without problems. Thanks to the guidance of the theory, we constructed a stable demonstration without working overtime, because we have a good understanding of each impact factor. Later, some preliminary results of our sensor selection method were presented at the 2007 IEEE Sarnoff Symposium at Princeton University and we won 3rd Best Paper Prize in the student paper/poster competition session.

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[1] As will be explained later, the two matrices are not only tightly connected in concept but also equivalent in many cases. In this book, unless explicitly stated, we usually use the term FIM to refer to the two matrices.

The lesson that we learned from our WSN design experiences is that a math tool that supports quantitatively analysis of the impact of various factors on the observation error is of vital importance to assure the reliability of the sensor network systems. So far, the FIM seems to be the best candidate for this purpose.

1.2 Summary of Contributions

In this book, several WSN problems are unified under the framework of OED, where the FIM plays an important role. The essential contributions include the following:

- Formulate and solve a wide spectrum of cyber-physical observation system design problems based on FIM.
- We practiced this design methodology on our projects. According to our experiences, the FIM-based design is very helpful to secure the precision and robustness of the observation systems.
- Propose a numerical method to optimize the trajectories of mobile sensor nodes to estimate parameters of DPSs.
- Propose a class of sensor selection methods, namely convex optimal sensor selection (COSS), to select the "just-enough" number of sensors with the least communication energy cost for the optimal parameter estimation.
- Prove the existence of a class of implicit optimal sensor selection methods. The proof also provides guidance on the design of future sensor selection methods as well as the parameter tuning of those methods.
- Verify the robustness and performances of the sensor selection algorithm using extensive hardware experiments and simulations.
- Propose an asynchronous time difference of arrival (TDOA) localization method for energy efficient localization by WSNs.
- Based on the TDOA method, develop a method to optimize the beacon placement for robust localization.

1.3 Organization

The organization of the book is as the follows. In the rest of this chapter, we will introduce some concepts and math ground knowledge.

The mobile sensor trajectory optimization problem is discussed in Chap. 2, based on the context of MAS-net project. This is an example on how to apply the FIM on optimization problems which are modeled by partial differential equations (PDEs) and ordinary differential equations. In practice, static sensors and mobile sensors are cooperative rather than competitive.

We then naturally introduce an interesting and important design problem for static sensor networks: Chap. 3 focuses on the sensor selection problem (SSP). A just-enough sensor selection method is presented and analyzed. While many related