From Context Awareness to Socially Aware Computing

The new generation of smartphones has realized the early vision of context awareness. The next step is facilitating real-world impact of more complex recognition, moving toward next-generation opportunistic recognition configurations and large-scale ensembles of networked subsystems interacting with communities of users.

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The notion of systems adapting their functionality to a user's activity and the situation in the environment is an essential part of Marc Weiser's vision. Over the years, this notion has led to the concept of context awareness.[1,2] The early vision of context awareness included a proposal for mobile phones featuring acceleration and light sensors and offering the ability to recognize simple contexts—such as device position (on the table or in a pocket), modes of locomotion, and user location—and adapt their functionality accordingly.

Today, such visions of context awareness have become a reality in everyday products. Modern smartphones come equipped with sophisticated sensing capabilities, and a range applications exist that leverage simple context information, such as user location, motion state (jogging "loggers," for example), or the environmental noise level. Here, we discuss three key directions that will drive more ambitious recognition research in the future: moving beyond modes of locomotion and location to incorporate complex activity recognition into real-world applications; realizing opportunistic recognition configurations; and moving from a "single-system, single-user" perspective toward large-scale ensembles of networked systems interacting with communities of users.

Beyond Modes of Locomotion and Location

Researchers recognized early on that context is much more than simply recognizing motion states and location. Much research has since gone into recognizing a broad range of complex activities and situations. However, despite encouraging research results, the impact of such recognition on real-world applications has been rather small. The question is, why, and what can we do to change this?

The Challenges

We can't describe in detail here all the problems with real-world applications of complex activity recognition. Instead, we illustrate some of the key issues by looking at why recognizing modes of locomotion has been so successful. We contrast this success with another problem that has received a significant amount of attention in the research community but has had much less practical impact: the recognition of so-called *activities of daily living* (ADL).[3]

Recognizing compound activities. First of all, recognizing modes of locomotion is a well-defined,

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constrained problem. For a majority of applications, we can assume that there's a limited number of nonoverlapping, discriminant states—or "labels" in machine-learning terminology. With labels such as "sitting," "standing," "walking" (possibly including up and down), "running," "cycling," and "driving," almost all kinds of human motion in everyday situations are covered. Early research was guided by the assumption that a person walks, stands, or sits but never does two at the same time (although exceptions such as "sitting while driving" exist).

The ADL-based approach, on the other hand, is motivated by contextual activities and includes things such as housekeeping, meal preparation, and watching TV. Recognition labels here represent complex compound activities, some of which (housekeeping, for example) can be composed of numerous, diverse lower-level activities or concrete actions. Many of the activities can be executed in parallel (housekeeping and watching TV) or interleaved.

Accommodating high variability. As a second point, modes of locomotion have a distinct signature in an easily deployable sensor modality (acceleration or motion sensors in general). Activities like housekeeping, on the other hand, generally don't, because there's simply too much variability in the way they can be performed.

A common approach to this problem is to rely on highly instrumented environments. For example, many ADLs have a characteristic signature in terms of objects with which the user interacts.[4] Thus, putting an RFID tag on every relevant object in a household and an RFID reader on a user's wrist can produce good recognition results. Along the same lines, highly instrumented smart apartments can have binary sensors indicating the opening of every cabinet or even the removal of every object.[5] Adding sensors to water pipes and power lines can also be useful in ADL recognition.[6]

Despite some promising results, these approaches have had two problems. First, there's the question of the practicability of such extensive instrumentation (which we discuss later in more detail). Second, in many cases, the transfer of the results from one environment to another isn't straightforward. One person might use an electric kettle to warm water for tea, while another might get hot water from a coffee machine.

User-specific training. The third issue is the fact that modes of locomotion can be trained reasonably well in a user-independent way. This means that a smartphone app can be pretrained and delivered ready to use. For complex activities, on the other hand, good results are mostly achieved only with user- and environment-specific training. Therefore, the user might have to be given an app that doesn't initially work but "learns" upon use. Clearly, this can be a complex and tedious process.

Facilitating the real-world impact of complex activity recognition is a nontrivial problem that's likely to occupy the research community for a significant time.

Toward a Solution

Facilitating the real-world impact of complex activity recognition is a nontrivial problem that's likely to occupy the research community for a significant time. As with any advanced research, it's impossible to say in advance which approaches will succeed. However, there are some directions that, from past experience, are likely to prove highly relevant.

Activity models and high-level reasoning. As noted, major issues for both recognition algorithms and experimental methodology are the complex structure of human activity in general and the huge variety of high-level activities relevant for recognition. As a possible remedy, researchers have suggested decomposing complex activities into simpler ones in hierarchical reasoning approaches. For example, you might decompose vacuum cleaning into fetching the cleaner, switching it on, vacuuming, carrying it somewhere else, switching the device off, and putting it away. Vacuuming can further be described as a combination of walking, standing, and moving your arms. Thus, eventually, with a step-by-step decomposition, the recognition of complex activities can be reduced to the recognition of simple activities—such as modes of locomotion, simple motions, interaction with objects, and so on—followed by high-level reasoning over the results to determine the complex actions that they constitute.

Issues such as parallel and interleaved execution, variability, and need for user-specific training are less of a problem with simple activities, so although recognition isn't trivial (an example problem case would be the short, subtle motion of pushing a button), it's significantly easier than recognizing complex actions. In addition, although there's many possible high-level activities, on the lower level, a smaller number of activities—such as modes of locomotion, vocal activity, and interaction with the key object—are the main constituents from which most high-level activities are built.

At the same time, high-level reasoning is often done at the symbolic level, which is more meaningful to humans, and it offers a number of promising avenues for dealing with variability, user-dependent training, interleaving, and so on. Thus, for example, activity descriptions (including the range of possible variations) can be mined from the Web or contributed by users. For example, consider the user-contributed knowledge codified by the CommonSense system.[7] Another interesting aspect is that models of high-level activities can contribute to increasing the accuracy of the low-level actions on which they build by providing additional boundary conditions (action A must follow action B) and prior probabilities.[8]

Applying the hierarchical recognition approach would be much easier if there were a generally agreed upon taxonomy of activities that would specify a set of particularly relevant "key" activities (that is, activities that can be found in a broad range of applications) and models of the temporal and causal relations between them. Clearly, a complete and consistent taxonomy of human activity isn't feasible. Instead, the community must pragmatically focus on finding a set of activities that covers a significant portion of relevant applications (possibly different for different domains) and models that optimally support the recognition process. This is a different problem statement from the one in cognitive science, for example, which deals with explaining how humans think about and plan activities. Thus it isn't clear how far the existing body of work in the cognitive science field can be leveraged.

Standard datasets. Scientifically solid comparisons of different recognition methods are only possible if we can guarantee equal test conditions. Consequently, many pattern-recognition-related communities rely on standard benchmark datasets for this purpose. Unfortunately, activity recognition, so far, hasn't relied on such datasets, which makes a reliable evaluation of methods (crucial for wide-scale practical deployment) difficult.

Beyond a scientifically solid evaluation, large standardized public datasets, combined with the activity taxonomy mentioned earlier, could help the community deal with the issues of variability and user-specific training, facilitating faster development of reliable recognition. Thus, large community-collected datasets could reveal the type of variability expected from different environments and provide a corpus of reliable, representative training examples for low-level recognition systems.

Assuming we can reliably recognize complex activities in real-life environments, will that automatically lead to wide-scale adoption of context-aware systems?

Experimental procedures and description standards. Much activity-recognition work published to date is inherently difficult to replicate. Reproducibility of context-recognition research is always going to be a difficult issue. However, observing a set of generally accepted "best-practice guidelines" could significantly reduce the problem. There were many attempts in the community to define such standards (for example, the 2010 Pervasive Workshop on Activity Recognition Research), but the scientific community still hasn't reached a consensus.

Well-defined experimental procedures are also crucial for establishing standard datasets, which can make a significant contribution to moving complex activity toward real-world applications.

Better evaluation metrics. Given the complex nature of activities, proper evaluation metrics aren't obvious. Activities can, for example, be evaluated on a sensor-frame basis, event basis (the fact that somebody took a meal aggregated over all relevant time frames, for example), with and without timing information, or taking into account interleaving and parallel execution.[9] What type of evaluation is appropriate depends on the application, as does the question of what's adequate recognition performance. Currently, these factors aren't being sufficiently considered.

Beyond providing users with a more reliable assessment of the value of specific methods, better evaluation metrics can play an important role in improving recognition performance by providing more problem-oriented optimization criteria and a better understanding of where exactly algorithms fail. For example, a metric that correlates misclassifications with interleaved—instead of randomly distributed—execution makes optimizing an algorithm for a specific application much easier.

The bottom line. For complex-activity recognition to become relevant for real-life applications, the research field must mature and become much more like established areas such as computer vision or speech recognition. This also means that much more focus must be put on incremental improvements of algorithms. Such incremental improvements are generally valued as valid scientific contributions in fields such as computer vision and speech technology, but in pervasive computing, there's still significant ambiguity toward such work.

The Need for Opportunistic Systems

Assuming we can reliably recognize complex activities in real-life environments, will that automatically lead to wide-scale adoption of context-aware systems? At least one additional problem remains. State-of-the-art approaches to context recognition mostly assume fixed, narrowly defined system configurations dedicated to often equally narrowly defined tasks. Thus, for each application, the user must deploy and place specific sensors at certain well-defined locations in the environment or on his or her body. For universal context awareness, this approach isn't realistic. We need systems that can exploit devices that just "happen" to be in the environment.

A fundamental assumption underlying the majority of context-aware systems are "purposeful" sensor-system configurations, often deployed according to the requirements and nature of a given application. Clearly, here the recognition methodology (multisensor fusion, feature extraction, and classification) determines the number, capability, data rate, and placement of sensors at design time. Recognition accuracy is known to depend on carefully chosen and tuned features and algorithms trained on representative datasets. From a practicability viewpoint, the design-time sensing-system assumption is supported by Mark Weiser's vision of electronics (including sensing) invisibly becoming omnipresent in our environment—if plentiful sensing will be everywhere, then surely the sensor system that a given application needs should also be easily available. The argument is often backed up by showing that the proposed sensor setup is cheap and easy to deploy and maintain. A good example is miniaturized motion sensors unobtrusively integrated into clothing (such as the Hug Shirt; www.cutecircuit.com/products/thehugshirt).

However, the availability of sensor-enabled shirts doesn't mean that a significant number of people will be regularly wearing them. People might have at most a few such shirts—probably each with a different sensor combination—and they wouldn't always be wearing one. In general, widespread sensor availability doesn't necessarily mean that an application can assume that required sensors will continuously be available in the same configuration. Instead, we must assume that as the user moves around, he or she is at times in highly instrumented environments, where a lot of information sources are available. At other times, he or she might stay in places with little or no intelligent infrastructure. Concerning on-body sensing, the best we can realistically expect is that at any given point in time, the user carries a more or less random collection of sensor-enabled devices (such as a mobile phone, watch, or headset) on different body locations (in different pockets, on a wrist, or in a bag).

Consequently, the methodological approach for context recognition reverses: sensors are no longer purposefully deployed to satisfy the data needs for recognition algorithms and applications. Instead, we can assume that the sensors are there, and recognition algorithms and applications can make appropriate use of them as needed. We thus speak of an opportunistic recognition system.

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Opportunistic, Goal-Driven System Management

In an opportunistic system, how we think about sensors and the process of sensing must be reversed: everything is a sensor! The basis for this thinking is to consider every source of data (by using a standardized access interface) as an abstract sensor.[10] Aside from the "classic" understanding of a sensor represented by a miniaturized unit of hardware, a variety of different, abstract sensors are considered. These include online sensors (such as Twitter feeds or Facebook updates), harvest sensors (which can collect and locally store data), playback sensors (which can generate data streams from repositories), and synthetic sensors (which provide simulated data based on a model of real-world processes).

Abstracting all kinds of information sources into generic sensor categories providing standardized access interfaces is the key to opportunistic sensing. Following such an approach, researchers are pursuing the idea of goal-oriented sensor assemblies that configure spontaneously to achieve a common activity- or context-recognition goal, without requiring a predefined sensor infrastructure or fixed recognition goal to be defined at design time.[11] To this end, self-describing sensor markups—as well as sensor-interface abstractions—need to be preserved, involving both physical hardware devices as well as immaterial sensors (such as online-accessible sources or sensor-simulating software entities). Mechanisms for sensor-ensemble configuration based on possibly competing or complementary sensing capabilities are also sought that respect cost and resources: among many possible ensembles, the ones that involve the least amount of resources (communication, energy, compute power, and so on) would be preferred.

Classification in Opportunistic Sensor Systems

Although sensor abstractions and self-description markups, as well as spontaneous (wireless) solicitation of sensor services, appear feasible with state-of-the art technology,[10] the classification capabilities of sensors and spontaneous sensor configurations remain crucial. Here, the vision presented in the previous section elegantly fits with the notion of an activity taxonomy and the recognition of complex activities through reasoning over a set of basic activity components.

We can imagine sensor nodes offering not just signals and simple preprocessing but also algorithms for the recognition of basic activities. On the other hand, we could imagine recognition systems that reason over standardized signals from abstract sensors. Clearly, this only works if we can assume that a set of basic activities and abstract features is relevant across a range of applications and situations. Of course, finding such a set is a challenge, but experience indicates that it might be feasible.

Thus, things like modes of locomotion, vocal interaction (speaking versus not speaking), and interaction with common devices and objects reoccur across many scenarios. On a lower level, human motions are constrained by physical boundary conditions, and we could well imagine a set of primitives as abstract sensors.

Another promising approach is to have sensors and systems accumulate and exchange experiences about successful sensing missions for the recognition of activities in nonsupervised learning procedures. This information, when shared among sensors ("transfer learning"), could lay the groundwork for new techniques on opportunistic "informed" sensing. The Opportunity research project (www.opportunity-project.eu) recently demonstrated that a "sensing experience" made by a certain individual sensor or a sensor ensemble can be abstracted and transferred to other, maybe even next-generation (future) sensors. These findings give inspiration for an evolution of learning sensors, which might not only sustain but even extend sensing capabilities from one generation of technical sensors to the next.

Socially Aware Computing

Our vision as discussed so far implies that, eventually, the environment will be full of users equipped with devices that can reliably perform complex activity recognition. Furthermore, every device will be "willing" and able to identify and exploit potential information sources in its neighborhood. Clearly, such sources might not only be sensors but also other context-aware systems.

What happens if, instead of considering each device for itself, we look at them as a collaborating collective? This opens up three opportunities for what we refer to as "socially aware computing:"

1. novel, more powerful methods for monitoring and analyzing social interactions—in particular, with respect to long-term interactions and interactions within large communities and organizations;
2. subsuming the information from many individual interactions into models of aggregate human behavior and social dynamics; and
3. developing collaborative, "social" algorithms for the recognition process itself.

Socially aware computing is related to the recent trend of leveraging people's mobile phones for large-scale, mobile sensing. Examples include monitoring traffic congestion, commuting patterns, or even potholes on roads.[12] An elegant description of such applications has been put forward by the MetroSense project, which envisions "urban sensing at the edge of the Internet, at very large scale" or "people-centric sensing."[13] However, socially aware computing is about more than the mere scale of sensing. Instead, it allows fundamentally new types of applications, extending the notion of context awareness into a different domain.

Sensing Social Interactions

Interactions between users have long been considered an important part of context. However, early work focused on looking at signals from a system of a single user to establish the type of social activity in which he or she could be engaged. Typically, user location, motion patterns, and vocal behavior would be used to determine the type of social context in which the user was engaged (for example, at a meeting, at a party, or alone). Consider the goal of developing a smartphone that knows when to ring rather than vibrate. This legendary pervasive computing problem, postulated early on, at first sounded relatively simple to solve (initial attempts using simple parameters such as environmental sound level or user location). However, despite some success,[14] a truly satisfactory solution has so far remained elusive. This is because it requires an elaborate understanding of the social context.

Leveraging collaborative analysis to "reality mine" information from many users collected continuously during everyday interactions can reveal a much more detailed and subtle picture of social interactions. Such a picture offers a new level of insight into the problems of industry and government, including building customer relationships, logistics and resource management, transportation, and public health.

Consider reality mining mobile-phone GPS data, call logs, and email records to better understand "traffic" within an organization. Analyzing these digital traces creates a detailed picture of face-to-face, voice, and digital communication patterns.

Variations in patterns of communication between workgroups typically account for roughly 40 percent of the differences in productivity. The main pattern of communication that determines productivity is known in the sociology literature as the *network constraint*: the extent to which the people you talk to also talk to each other, as averaged over all the members of a work group. Moreover, patterns of change within these communication networks are also a critical predictor of creative productivity and are sometimes the largest factor determining differences in creative output.

The most significant communication pattern for determining creative output is a combination of the network constraint (cohesive communication within the workgroup) and periods of exploration to spend time with different workgroups. As illustrated in Figure 1, a German bank achieved significant improvements in performance just by relocating a previously orphaned "customer service" group (labeled "CService," mostly communicating by email in the original setup) to facilitate more face to face communication. This simple, inexpensive change made sure that that everyone was "in the loop."[15]

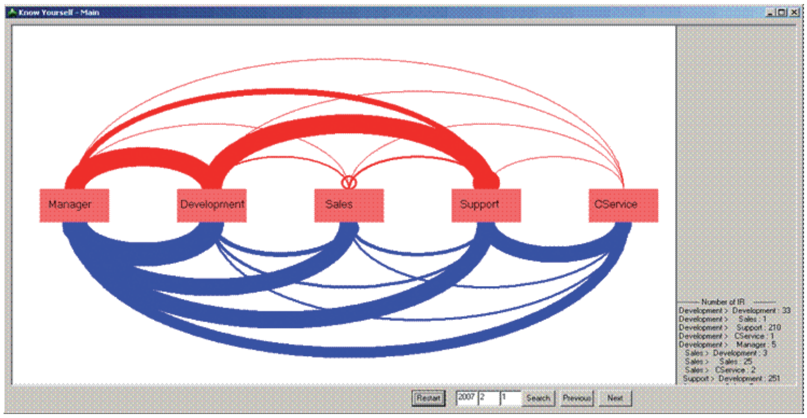

Figure 1. The pattern of face-to-face and email communication in a German bank. The thickness of the top arcs (in red) shows the amount of face-to-face communication, while the thickness of the bottom arcs (in blue) shows the amount of email communication. In our studies of many different types of companies, we found that the patterns of face-to-face and email communication is a critical predictor of both productivity and job satisfaction.

Sensing Social Phenomena

Extrapolating these ideas even further leads to the analysis of not just the social interactions of an individual but to second-by-second models of group dynamics and reactions over extended periods of time, providing dynamic, structural, and content information. The key is to harness these streams of personal data and use them to create and drive dynamic models of aggregate human behavior.[16] Applications include the discovery of opinion and lifestyle shifts, demographic trends or urban development, and public health.

Example: public health beyond static demographics. Most government health services rely on demographic data to guide service delivery. Demographic characteristics, however, are a relatively poor predictor of individual behavior. The major determinant of many health outcomes is behavior—more so than wealth, age, or place of residence.

The pattern of movement between the places a person lives, eats, works, and hangs out are known as a *mobility behavior pattern*. Reality-mining research has shown that most people have only a small repertoire of these behavior patterns ("eigenbehaviors"), and that mixtures of this small set of behavior patterns account for the vast majority of an individual's daily and weekly mobility patterns.[17]

(a) (b)

Figure 2. Clustering together people with similar behavior patterns helps uncover largely independent subgroups in a population. (a) Movement patterns as transitions between the most popular hangouts—bars, restaurants, and similar locations. The hangouts are shown as dots, color-coded by the different subpopulations that typically visit the destination, where the subpopulations are defined by clustering their mobility behavior. (b) A transition graph showing the typical transitions between different destinations, again color-coded by the different mobility subpopulations. This graph illustrates that the mixing between these subpopulations is surprisingly small. (Figure courtesy of Sense Networks.)

Using mobile phone traces, we can also cluster together people with similar behavior patterns to discover largely independent subgroups in a population, which we refer to as *subpopulations* (see Figure 2).

Knowing the mobility behavior of different subpopulations provides a far

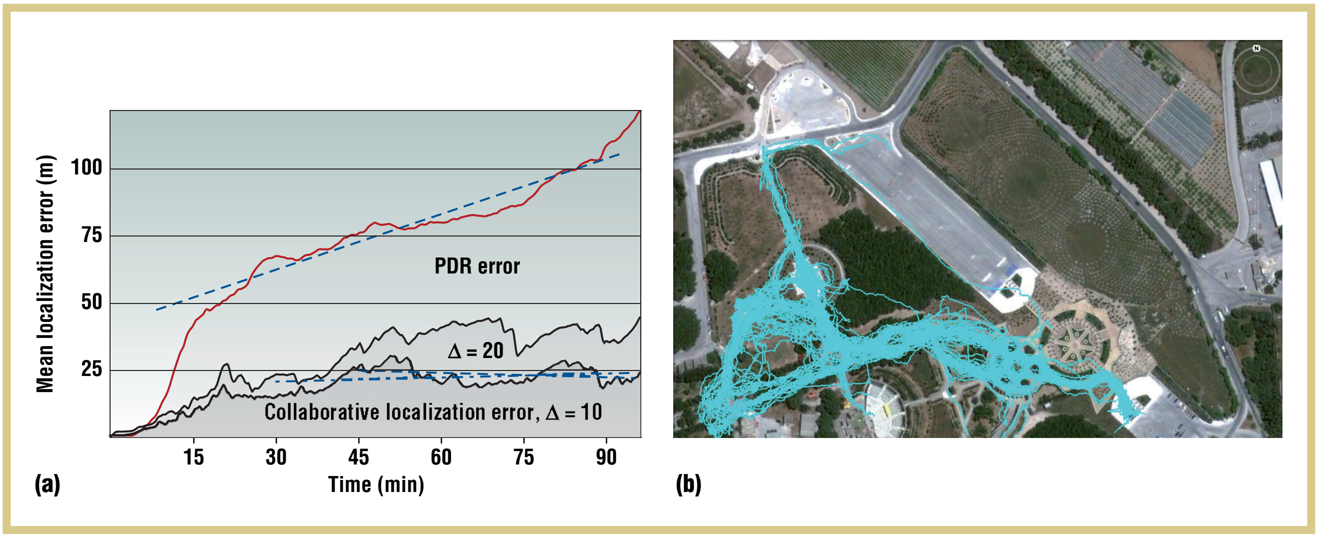

Figure 3. Transition of a collaborative pedestrian dead reckoning (PDR) system from the unbounded to constant-error phase when enough devices use proximity information to correct their estimate.[21] (a) The average error as a function of the distance walked for the noncollaborative (upper unbounded curve) and collaborative (lower bounded curves). (b) The traces used for the analysis—over 60 km of tracks from an open air festival in Malta.

more accurate picture of their preferences and risks than does standard demographic information. Such a segmentation of the population into different "behavior demographics" has been experimentally shown to provide between five and 10 times the accuracy of traditional demographics at tasks such as predicting potential for diseases of behavior, financial risk profiles, consumer preferences, and political views.[18]

To understand this, consider diseases of behavior, such as diabetes. It makes sense that the types of restaurants you go to, the frequency of walking, and similar patterns of behavior strongly influence your risk for diabetes. Similarly, consumer preferences are likely to be widely shared among a subpopulation that enjoys the same entertainment and chooses the same types of dining establishments.

Even greater accuracy at modeling human behavior patterns can be obtained by adding credit card data, healthcare information, and similar "digital breadcrumbs."

Example: sensing crowds. Sensor-based analysis can also be used to understand physical interactions in human collectives. As a simple example, we demonstrated how the analysis of Bluetooth device density in one's environment can be used to estimate crowd density.[19] The method is based on scanning the environment for discoverable devices and computing a range of features, such as the number of discovered devices, temporal variations of that number, average signal strength, and signal strength variance.

Although the general principle is simple and builds on a large body of work using Bluetooth for co-location sensing, it underscores the argument for collaborative analysis of data from many devices. Looking at four crowd-density classes (0.1, 0.2, 0.3, and 0.4 people/sq m) in a dataset from the Munich Octoberfest, we achieve a recognition accuracy of 63 percent using data from a single device. By computing collaborative features that take into account data from several co-located phones, this can be improved to 83 percent. In addition, correlating data from several devices can provide information on crowd motion (from the change in the "seen" devices) and even track individual users.

Martin Wirz and his colleagues have proposed a method for detecting more complex crowd phenomena, such as flocking or queuing.[20] Their method relies on correlations between signals from body-worn motion sensors to determine patterns of users walking together.

Collaborative, Socially Inspired Sensing and Recognition

Pervasive sensor systems collaborating in complex, dynamic ways could help us discover complex social dynamics. At the same time, they're increasingly themselves becoming subject to the laws and phenomena governing such dynamics, as the dynamics of the collective sensing devices start to look like the dynamics of human collectives. Figure 3 explains the average error of inertial indoor navigation systems (such as pedestrian dead reckoning, or PDR) based on smartphone sensors. By their very nature, such systems accumulate error in an unbounded way.

We investigated how much this error can be reduced if we can detect when two people are in proximity of each other and can use the proximity information to correct the position estimate of their individual PDR system.[21] The DFKI group showed that there's a critical frequency for such corrective "calibration" meetings, where the system state is readjusted so that the average error remains constant. Thus, in essence, we have a phase transition-like behavior commonly found in dynamic complex systems. Such systems don't display continuous change. Instead, when a given system parameter (in our case, the frequency of calibrations) reaches a certain critical value, they "jump" into a state with qualitatively different properties (in our case, a state where the error remains bounded instead of increasing toward infinity). In fact, system behavior can be described by mathematical models commonly used in population dynamics and epidemic analysis.

Another example of activity-recognition methods that involve a social component has been described by Nicholas Lane and his colleagues.[22] Their work addresses one of the key challenges to the real-world impact of activity recognition described in the introduction: the need for user-specific training. It proposes leveraging social-network connections to identify users whose behavior is similar enough to facilitate the sharing of pretrained classification models and labeled training data. The authors analyze formal friendship relationships, co-location history, and temporal co-occurrence. They show that sharing training data and models between users found to be similar according to their methods leads to better classification accuracy than either randomly sharing data between the users or using classifiers trained on data from all users. The significance lies in "closing the loop" from (on the one side) activity recognition, enabling the recognition of social interaction back to (on the other side) the knowledge of social interactions improving activity-recognition methods. In addition, it illustrates the connection between socially aware computing and social networks.

Overall, using collective sensing to investigate social dynamics involves more than working with the established signal-processing and pattern-analysis methods underlying most context-recognition applications. Instead, traditional machine-learning methods must be combined with complexity theory and social science to develop a deeper understanding of the underlying phenomena. Such a multidisciplinary approach is part of the EU FuturICT project's focus, which we're all involved with (www.futurict.eu).

We envision moving toward reliable, practicable recognition of complex contexts and activities and performing such recognition using dynamically changing, a priori, unknown system configurations in virtually any real-life setting. From there, we'll transition to recognizing social contexts, community-level situations, and collective human behaviors. The latter will facilitate socially aware and adaptive computing as the logical next step from context awareness. This doesn't mean that the original sense of context awareness will become obsolete. It merely shows the opportunities of going beyond the traditional notion of context.

However, with such opportunity comes the challenge of addressing questions of privacy and data ownership.[5] Advances in analysis of user-related data must be approached in tandem with an understanding of how to create value for data producers and owners while still protecting the public good.

The required degree of individual control over personal data might sound quixotic, and in the case of the "anything goes" world of online social media, there are many difficulties. However, in regulated industries—wireless carriers, banks, healthcare providers, and so on—there's real hope.

For example, one of us (Alex Pentland) has helped initiate and curate a discussion among leading regulators, CEOs, and advocacy groups within the World Economic Forum, which has obtained broad agreement on a set of general principles.

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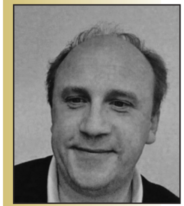

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