Human-Attention Inspired Resource Allocation for Heterogeneous Sensors in the Web of Things

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A heterogeneous sensor-based Web of Things system model with ubiquitous attributes and a human attention-inspired resource allocation scheme facilitates dynamic resource interaction.

The Web of Things (WoT) addresses pervasive integrations of ubiquitous sensing, internetworking, and intelligent management, enhancing the things' Web-based interconnections.[1] The WoT is evolving toward a massive data-, knowledge-, and information-oriented cyber-physical-social space involving increased physical perceptions, cyber interactions, and social correlations in resource-constrained environments.

The WoT is expected to be a hyper-ecosystem that realizes an organic amalgamation and harmonious symbiosis among physical and cyber things and human society, and provides data-cycle-based wisdom.[2] In moving toward Web-based ubiquitous intelligence, the cyber-individual is an attractive concept realizing brain-informatics-based holistic wisdom that considers the harmonious symbiosis of the ubiquitous things and the human.[3] The unit and ubiquitous Internet of Things introduces a human-like nervous system architecture and social-organization framework in an effort to create a system paradigm, establishing the things' online

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interconnections.[4] It presents an attractive perspective when addressing WoT issues by imitating human intelligence and cognition.

Existing resource solutions in the WoT mainly focus on architecture design and traditional algorithm redesign, referring to online resource management,[5] constrained resource allocation,[6] distributed resource sharing,[7] and bio-inspired resource saving.[8] WoT resource research is still in its infancy, and unique insights become necessary for resource management. Human cognitive competence might be potentially available for addressing Web resource issues. In the WoT, ubiquitous resources are assigned with challenging requirements:

- *Semantic resource description.* Cyber resources (for example, data, knowledge, information, and services) tend to be organized by semantic interconnection and intelligent aggregation. Resource descriptions should be supported by a semantic-centric perspective with collective intelligence, cooperative ontology, and dynamic authoring.
- *On-demand resource distribution.* User-driven virtual resources are an emerging orientation for on-demand resource provision, which dynamically allocates the actual resources within networked clouds to tailor the optimal resource algorithms for virtual resource mapping.
- *Spontaneous resource discovery.* Web-services-oriented resource discovery facilitates network virtualization and information dissemination. Autonomous resource-searching mechanisms can be adopted during the distributed spontaneous resource discovery.
- *Cooperative resource sharing.* Resources are interoperated by multiple owners to achieve enhanced resource sharing and resource use in the scalable contexts, and are aggregated for aggregated functionality cooperation.

In this article, we apply analogies from human cognition to establish an attention-aware resource framework and present a human attention-inspired resource allocation scheme for WoT applications.

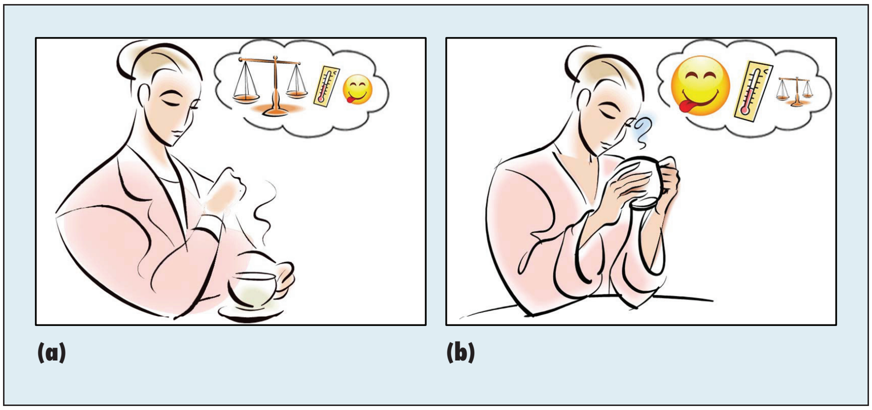

Figure 1. An example of having a cup of coffee with dynamic attention. When the person is (a) holding the cup of coffee, she might consider its weight, and when (b) drinking from the cup, she might think about the coffee's taste or temperature.

Attention-Aware Resource Framework

In the WoT, attention is a limited resource due to the explosions of perception, connection, and service, and is becoming more precious during resource management. Instead of objective reflections on the cyber-physical-social space, attention is more likely to create new perspectives on resource interactions during intentional activity. Figure 1 illustrates an example of having a cup of coffee. In the figure, the person holds and drinks a cup of coffee, during which the person considers different aspects of the coffee itself. When the subject first sees the cup, she might subconsciously sense the coffee's weight. Upon taking the first sip, she might pay more attention to the coffee's taste or temperature. Here, multisensory organs (for example, hands, eyes, and tongue) are invoked for dynamic attention allocation. Using the main characteristics of human attention—including stability, extendability, allocability, and transitivity[9]—it's possible to adopt the elements of human cognition to address the WoT resource issues.

Web resources mainly cover the cyber-physical-social resources referring to ubiquitous things—including physical objects (for example, sensors), cyber-entities (for example, cloud servers), and associated social attributes (for example, ownership and affiliation relationship). The characteristics of abstract human attention can be applied to support the cyber-physical-social resources for providing various functions during interactions to achieve service access, discovery, and sharing.

Attention as a Limited Cognitive Resource

Attention mainly refers to sustained attention, selective attention, and divided attention, which is a limited resource to satisfy the human cognitive rules.

Sustained attention. A human uses sustained attention to address a cognitive thing (such as an object or activity) for a prolonged time. During sustained attention, the attention is obtained, held, and released. Humans engage this type of attention to complete cognitively planned or sequenced tasks for efficient information processing, in which a distraction might arise, interrupt, and interfere. When people have less sustained attention, they usually have an accompanying inability to control their behaviors (such as inappropriate behavior inhibition and distraction avoidance) or to adapt to environmental requirements.

Selective attention. Selective attention concentrates the resource on a specific aspect in the internal or external environment and simultaneously disregards others. Here, an available attentional state is limited in time, therefore the mind subconsciously filters out other unnecessary or unimportant issues. For example, the cocktail party effect is the phenomenon of focusing one's auditory attention on a particular stimulus while filtering out a range of other stimuli, enabling a partygoer to follow a single conversation in a noisy room. The Stroop effect addresses the psychological difficulty in selective attention in identifying a color name printed in a color not denoted by the name. Comprehensive effects immediately detect sensitive information originating from the unattended stimuli, and different factors drive the attention selection.

The top-down endogenous processing and bottom-up exogenous processing can jointly address attention acquisition:

- Endogenous goal-driven attention processing steers attention toward the subjectively important stimuli themselves, for instance, to read a book on a running bus while ignoring the ongoing road traffic.
- Exogenous stimulus-driven attention processing brings attention to potentially important stimuli in the environment, and can be automatically activated by a sudden stimulus.

It would be deleterious if attention was exclusively driven by an endogenous factor. Even when a person is concentrating on a book, attention should be open to salient external situations (such as the bus arriving at its destination). Similarly, it would be damaging if attention was controlled only by an exogenous factor, making it almost impossible to achieve directed behaviors without necessary and constant attention distracters. Endogenous and exogenous attention should be interactive, and a perfect trade-off of internally and externally driven attention is crucial for event execution.

Divided attention. Divided attention occurs when people actively pay attention to simultaneous tasks. That is, when people perform multiple tasks, they can divide their attention, either performing each task with weakened task performance or proficient performance with automaticity. Examples include driving a car while listening to the radio, and carrying on a conversation while eating dinner. During the simultaneous task execution, attention performance on at least one of the tasks usually declines due to the limited capacity to process information. Such attention performance can be improved with practice to achieve higher accuracy and lower response time. It's necessary to optimize the potential resource sources and provide support on the relative priorities of tasks to facilitate optimal attentional strategies.

Attention resource rules. The attention resource inherits the cognitive rules in cognitive psychology and satisfies the following rules:

- *Filter or bottleneck rule.* There are early selection, early attenuation, and late selection models to realize selective information processing. People filter environmental information and stimuli via feature detection, extraction, and identification, in which a bottleneck is applied to filter out information not selected for data processing.
- *Central resource capacity rule.* A single undifferentiated attentional resource is assigned to all possible multiple tasks, and the available attention varies mainly depending on dynamic tasks, environmental situations, and individual conditions. Along with demands increasing, supply of the attention resource increases until there is no sufficient resource for compensation. During performance of parallel tasks based on a single resource, this rule should ensure the completion of at least one task.
- *Multiple resource rule.* There are multiple sources from which the attention resource is allocated. Such a resource is differentiated according to specific processing components (for example, processing stages, perceptual modality, and processing codes). Performance of simultaneous multiple tasks depends on the competition for a common attention resource within multiple sources.

Figure 2 shows an attention-aware resource framework, referring to the abstract human attention and cyber-physical-social resources in the unit WoT and ubiquitous WoT.

Cyber-Physical-Social Resources in the Unit WoT

In the unit WoT, intraresource-oriented management modes provide services for a single application:

- *Active mode* is launched by the endogenous attention type to achieve an internal resource scheduling of activities. Predetermined instructions (for example, priority setting and abnormal response) can control the endogenous attention factors. Metaphorically, the active resource mode is like a human's conditioned reflex, which is acquired by repetitive training. In the active mode, things take obvious, subjective initiative on the basis of historical experiences. For instance, dynamic channel allocation is an active handoff control mechanism that guarantees quality of service and high bandwidth for multimedia traffic in mobile, wireless networks.

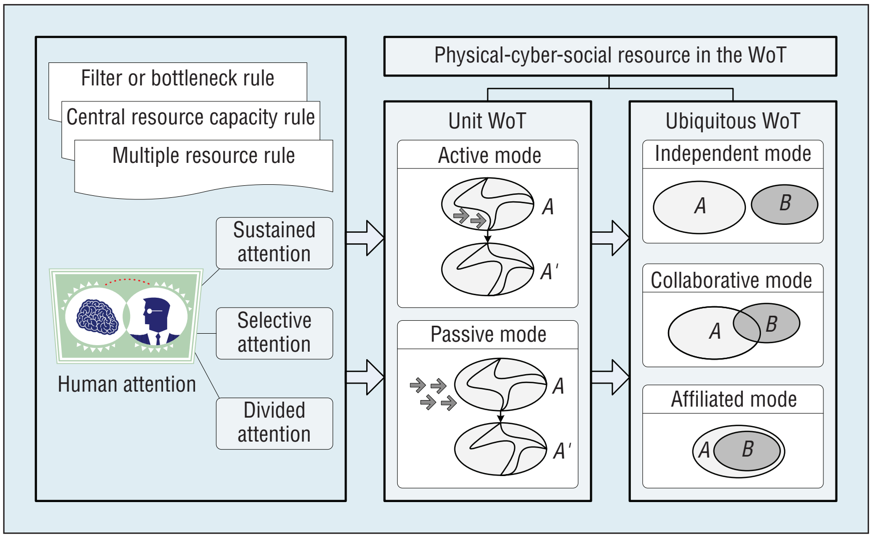

Figure 2. The attention-aware resource framework in the Web of Things (WoT). The rules of human attention can be introduced for resource allocation in the WoT. The cyber-physical-social resources refer to active/passive modes in the unit WoT and independent/collaborative/affiliated modes in the ubiquitous WoT.

- *Passive mode* is driven by an external behavior, event, or environment, and the exogenous attention plays a decisive role. Similarly, the passive resource mode resembles a human's unconditioned, stimulus-triggered response, with inherent factors having a greater influence on resource distribution. For instance, the on-demand resource provisioning is dispatched according to a preferential request in cloud computing and storage.

Cyber-Physical-Social Resources in the Ubiquitous WoT

Ubiquitous WoT covers multiple-unit WoTs, and the available resources establish interconnections to realize pervasive, seamless, and transparent access to the heterogeneous services. We can categorize interresource-oriented resource management into three modes:

- *Independent mode* indicates that the resource domains of the two WoT applications have no obvious interrelationships. For instance, different identity information might belong to independent resources referring to the physical object-oriented identifiers (for example, quick response and electronic product codes) and URIs (including locators and names).
- *Collaborative mode* means that the two resource domains might overlap. Resources that overlap share resources and those that don't overlap have private resources. In mobile, social networks, different applications can access an individual's data (for example, user preference and location information). For instance, Foursquare and TripIt could share location-related services. The resources might exist in collaborative interactions for promoting interoperable services in a service-oriented architecture.
- *Affiliated mode* denotes that a resource domain is affiliated with another resource domain. For instance, resources in cloud services could be established via Web-service application programming interfaces, cloud storage gateways, and user interfaces that are organized in the affiliated resource mode. In cloud storage, user data is stored in virtualized storage resource pools managed by trusted third parties. The storage capacity of an individual user and a cloud-service operator satisfies the affiliation relationship, by which the user can obtain an expandable storage capacity from the cloud service. It virtualizes the online storage resources as a common pool according to dynamic user requirements.

Heterogeneous Sensor-Based WoT

In the WoT, heterogenous sensors are deployed for comprehensive perception so that the ubiquitous things realize interconnections through the cyber-physical-social space.

Cyber-Physical-Social Cross-Space Mapping

The ubiquitous things as the main form of resources include physical objects and cyber-entities, which establish cyber-physical-social mapping in the WoT. A physical object is assigned with heterogeneous attributes that act as feature signals to inform the sensors. The sensors resemble dendrites of a neuron when detecting attributes of things. The things have the following characteristics:

- *Heterogeneous attribute matching.* The physical objects' heterogeneous attributes and the sensors' perception capabilities should be appropriately matched; only the adaptive sensors can detect the appointed attributes. The cyber-entities can be described by semantic-representation-based formal languages (for example, XML and OWL).
- *Space–time consistency.* The physical objects and cyber-entities establish interactions beyond the space–time constraints. A physical object can invoke the associated cyber-entities for resources, and a cyber-entity might interact with other cyber-entities to discover available resources for sharing. Additionally, space–time issues (for example, synchronization and correlation) should be considered during cross-space mapping.

- *Pervasive connection convergence.* The things exist in the context of pervasive interconnections, including the real communication networking via switches, routers, gateways, and other network components, as well as the virtual social networking via social-relationship-based online platforms. The connection convergence realizes the aggregated effects to provide enhanced services (for example, GIS, cloud services, and intelligent decision support).

Network framework

In the WoT, the network framework includes loosely coupled distributed-network components—that is, the sensor and Web-based networks.

The sensor networks cover both wired and wireless sensing networks, and the prosperity of wireless communications promotes the prevalence of wireless sensing technologies. Here, wireless sensor networks, near-field communication, and other communication types provide flexible network accessing patterns to strengthen local interconnections. The sensor networks use the existing physical infrastructure to connect independent terminal sensors and access nodes to provide data aggregation and actuator control services. Cognitive sensing is expected to proactively perform the data collection, object identification, information acquisition, and task execution. It integrates the sensor coordination and data fusion mechanisms to access, retrieve, and communicate with disparate sensors in a self-organizing manner to provide dynamic decisions and intelligent services.

The Web-based networks provide persistent online services, for which the access nodes are connected with hierarchical data centers via the Internet, mobile communications, and other network infrastructures, to achieve global interconnections. The WoT accelerates the evolution of the Internet and Internet Protocol version 6 over low-power wireless personal area networks, enabling IPv6 packet transmission over IEEE 802.15.4 networks, and letting low-power devices with limited processing capabilities participate in the WoT.

Human Attention-Inspired Resource Allocation in the WoT

Figure 3 shows a human attention-inspired resource allocation scheme for dynamic resource interactions in the WoT. The scheme refers to the physical objects (for example, sensors, and actuators), cyber-entities (for example, online resources), and the associated social correlation in the cyber-physical-social space. The heterogeneous attributes (marked as the geometrical shapes) are attached to the things in the physical space, and the sustained, selective, and divided attention is introduced during resource allocation. When the sensors detect stimuli triggered by the things' attributes, the corresponding actuators' sustained attention is disarranged. The selective attention is accordingly launched to perform an adaptive selection, and some attributes can be ignored. For the selected attributes, divided attention dynamically varies during resource interactions. The Web-based resource pool provides common resource support for the involved physical objects. Here, we define attention arrays as follows:

- The prior attention vector considers sustained attention and is an initial parameter obtained by the historical, interactive data with a self-updating capacity.
- The posterior attention matrix considers selective and divided attention and is a multidimensional array with a set of time-sensitive parameters obtained by real-time data collection in an ongoing session.

In the scheme, the related parameters include the following:

- *Attention array parameters.* $\{V_{1\times n}, V'_{1\times n}\}$ $(n \in N^*)$ are the initial and updated prior attention vector. $S_{T\times n}$ $(T \in N^*)$ is the dynamic sensing data set. $S'_{T\times n}$ is the revised sensing data according to a criterion. $E_{1\times n}$ denotes the sensitivity on heterogeneous attributes. $M_{T\times n}$ is the posterior attention matrix.
- *Attention distribution parameters.* $\{p_{V(i)}, p_{SE(i)}\}$ are the weight percentages of $\{V_{1\times n}, M_{T\times n}\}$ at the time point T_i. $\Delta\varphi_{(i)}$ is the aggregated variation between the posterior and prior attention at T_i.
- *Normalization parameters.* $\{n_{1ij}, n_{2ij}\}$ are the normalized values respectively satisfying Gauss distribution and uniform distribution. $R_{T\times n}$ is the resource allocation value. $R'_{T\times n}$ is the resource allocation percentage.
- *Optimization parameters.* $f(x)$ is an objective function for determining $\min f(x) = V_{1\times n}$, in which the variable x is a vector. $\nabla f(x)$ is the gradient of $f(x)$. $\{\alpha, d\}$ are search distance (that is, step length) and search direction of $f(x)$.

Prior Attention Vector Initialization

Assume that there are n heterogeneous sensors to capture the surrounding physical attributes. The prior attention vector $V_{1\times n} = [v_j]$ $(j = 1, \ldots, n)$, representing the predefined weight values of sensors, can be denoted in the variant form of

$$V_{1\times n} = \left[\frac{A_1}{A}, \frac{A_2}{A}, \ldots, \frac{A_n}{A}\right], \left(\sum_{j=1}^{n} A_j = A\right).$$

The gradient descent[10] is applied to determine $V_{1\times n}$. Let $f(x)$ $(x \in R^n)$

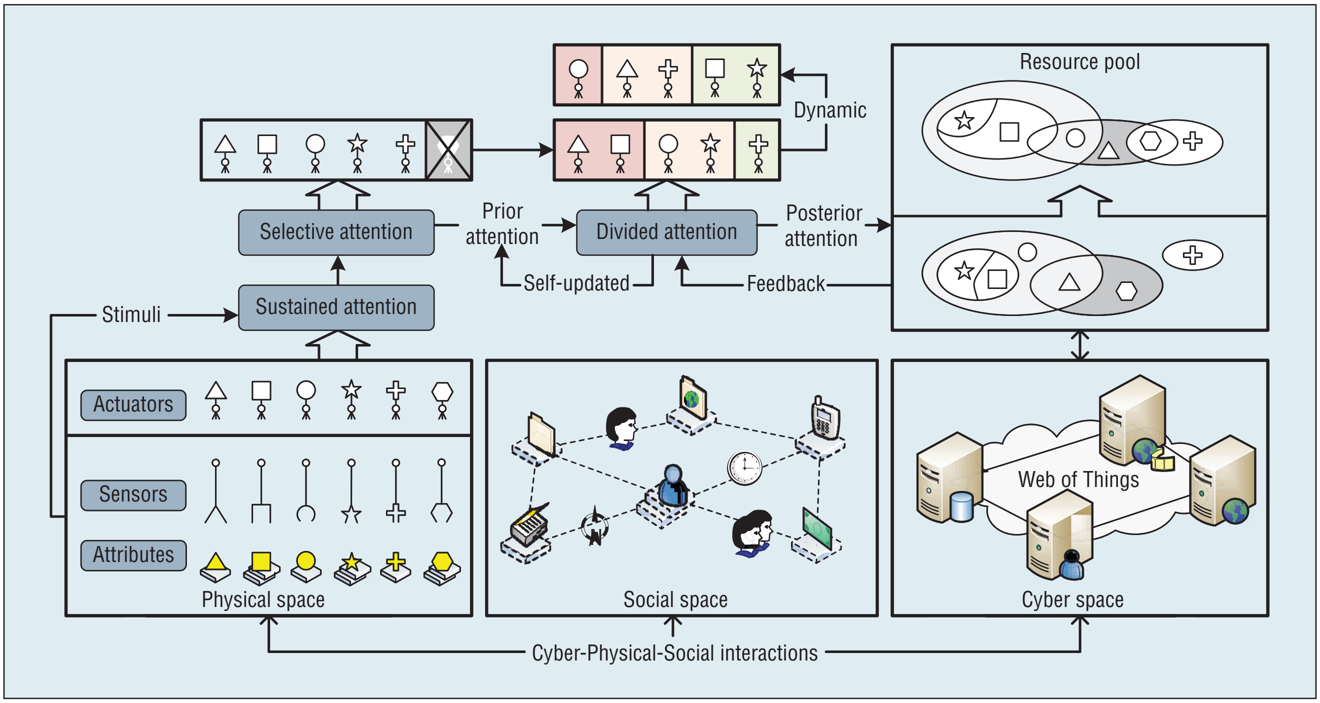

Figure 3. The human attention-inspired resource allocation scheme. The scheme refers to the physical objects (for example, sensors, and actuators), cyber-entities (for example, online resources), and the associated social correlation in the cyber-physical-social space.

be a first-order, continuously differentiable function and $d_k = -\nabla f(x_k)$ be the steepest descent direction to determine the minimum $\min f(x)$, with the iteration performed as follows:

1. Given a starting point $x_0 \in R$, and a sufficiently small value $\varepsilon > 0$, let $k := 0$.
   If $\|\nabla f(x_k)\| < \varepsilon$ holds, terminate the iteration to output x_k. Otherwise, continue the iteration.
2. Let $d_k = -\nabla f(x_k)$ and apply the Armijo inexact line search to determine an optimal step length α_k, which satisfies $f(x_k + \alpha_k d_k) = \min f(x_k + \alpha d_k)$. Let $x_{k+1} = x_k + \alpha_k d_k$ and $k := k + 1$, and go to Step 2.

In the Armijo line search,[10] the global minimizer of an univariate function $\phi(.)$ is defined as $\phi(\alpha) = f(x_k + \alpha d_k)$ $(\alpha > 0)$. Here, α_k satisfies the decrease condition $(c \in (0, 0.5))$: $\phi(\alpha_k) \leq \phi(0) + c\alpha_k\phi'(0)$. The Armijo line search is performed as follows.

1. If $\alpha_k = 1$ satisfies

$$f(x_k + \alpha_k d_k) \leq f(x_k) + c\alpha_k \nabla f(x_k)^{\mathrm{T}} d_k, \text{ let } \alpha_k = 1. \tag{1}$$

   Otherwise, go to Step 2.
2. Given constants $\beta > 0$ and $\rho \in (0, 1)$, let $\alpha_k = \beta$.
3. If α_k satisfies Equation 1, output α_k. Otherwise, go to Step 4.
4. Let $\alpha_k := \rho\alpha_{(k)}$, and go to Step 3.

Posterior Attention Matrix Assignment

During the dynamic interactions, $S_{T\times n} = [s_{ij}]$ $(i = 1, ..., T; j = 1, ..., n)$ persistently records the raw sensing data, and is further converted into $S'_{T\times n} = [s'_{ij}]$ according to a predefined criterion. $S'_{T\times n}$ and $E_{1\times n} = [e_j]$ are applied to define the posterior attention matrix $M_{T\times n} = [m_{ij}]$ for $m_{ij} = p_{SE(i)} s'_{ij}e_j + p_{V(i)}v_j$, and $p_{SE(i)} + p_{V(i)} = 1$.

Assume that the initial weight percentages $\{p_{SE(0)}, p_{V(0)}\}$ are assigned with the same value at the time point T_0. Toward the adjacent time points $\{T_i, T_{i+1}\}$, the percentages perform self-adjustment according to the practical conditions.

For $\Delta\varphi_{(i+1)} \neq \Delta\varphi_{(i)}$:

$$p_{SE(i+1)} = p_{SE(i)} + \frac{\Delta\varphi_{(i+1)} - \Delta\varphi_{(i)}}{\left|\Delta\varphi_{(i+1)} - \Delta\varphi_{(i)}\right|} \times v,$$

$$p_{V(i+1)} = p_{V(i)} - \frac{\Delta\varphi_{(i+1)} - \Delta\varphi_{(i)}}{\left|\Delta\varphi_{(i+1)} - \Delta\varphi_{(i)}\right|} \times v.$$

For $\Delta\varphi_{(i+1)} = \Delta\varphi_{(i)}$:

$$p_{SE(i+1)} = p_{SE(i)}, p_{V(i+1)} = p_{V(i)}.$$

Here, $\Delta\varphi_{(i)} = \sum_{j=1}^{n}\left|s'_{ij}e_j - v_j\right|$, and v is a unit variation value. Considering the posterior attention's reaction, $V_{1\times n}$ will be updated into $V'_{1\times n}$ after running a sensing session:

$$V'_{1\times n} = \left[v'_{1\times j}\right] = \left[\frac{A_j + m_{ij}}{A + \sum_{j=1}^{n} m_{ij}}\right].$$

Normalization and Resource Allocation

Normalization is performed to achieve a unified quality of the sensing data,

Table 1. Comparisons with the heuristic resource allocation algorithms.

Characteristics	Ant colony optimization	Genetic algorithm	Particle swarm optimization	Our scheme
Origin	Behavior of ants seeking a path between their colony and a source of food while leaving pheromone trails	Natural selection and genetics (for example, inheritance, mutation, selection, and crossover)	Behavior (for example, movement, and predator–prey behavior) of birds or fish	Human attention (sustained, selective, and divided)
Element factors	Maximum/minimum pheromone amounts, visibility, and Tabu search	Population size, fitness function, crossover probability, and mutation probability	Inertia weight, quasi-Newton method, and gradient descent	Prior attention vector, posterior attention matrix, and gradient descent
Feedback type	Positive	None	None	Positive
Advantages	Distributed parallelism, robustness, and compatibility	Randomness, robustness, and self-adapting	Dynamic neighborhood topology and high accuracy	Threshold controlled, dynamic, and lightweight
Shortcomings	Lack of initial pheromone, slow convergence speed, and search stagnation	Blind search, low efficiency, and limited convergence speed	Premature convergence and the local minimum	Dependence on historical experiences and limited applicability for massive networks

and the variables $\{n_{1ij}, n_{2ij}\}$ are applied to normalize the elements $[m_{ij}]$. Assume that n_{1ij} is a major factor satisfying the Gauss distribution, and n_{2ij} is a cofactor satisfying the uniform distribution.

Here, n_{1ij} represents the distance between m_{ij} and the arithmetic mean μ in units of the standard deviation σ.

$$n_{1ij} = \frac{1}{\sigma}(m_{ij} - \mu),$$
$$\left(\mu = \frac{1}{n}\sum_{j=1}^{n} m_{ij},\ \sigma\sqrt{\frac{1}{n}\sum_{j=1}^{n}(m_{ij} - \mu)^2}\right)$$

n_{2ij} is obtained by a linear function, in which the maximum value $m_i^{\max} = \max(m_{i1}, \ldots, m_{in})$ and the minimum value $m_i^{\min} = \min(m_{i1}, \ldots, m_{in})$ are used to measure m_{ij} into a nondimensional parameter:

$$n_{2ij} = \frac{m_{ij} - m_i^{\min}}{m_i^{\max} - m_i^{\min}}.$$

Based on dynamic attention, different weight coefficients are assigned to the heterogeneous attributes so that the resource allocation can be formalized in quantification. Two normalized values can be aggregated as $R_{T\times n} = [r_{ij}] = [pn_{1ij} + (1 - p)n_{2ij}]$ $(50\% < p < 100\%)$ to determine the resource allocation priority, in which $\{p, 1 - p\}$ are the proportions of $\{n_{1ij}, n_{2ij}\}$. $R_{T\times n}$ can be transformed into the resource allocation percentage $R'_{T\times n} = [r'_{ij}]$. The attributes with larger percentage will be assigned with higher share or priority to access more resources. Note that the resource allocation is not fully unrestricted. If the preassigned resource for one attribute exceeds a threshold T_d, the excess resource will be proportionally redistributed to other attributes.

For $r'_{ij} \le T_d$:

$$r'_{ij} = \frac{r_{ij} - 2\min(r_{ij})}{\sum_{j=1}^{n}(r_{ij} - 2\min(r_{ij}))}.$$

For $r'_{ij} > T_d$ $(\eta \neq j)$:

$$r'_{i\eta} = \frac{r_{i\eta} - 2\min(r_{i\eta})}{\sum_{\eta=1}^{n}(r_{i\eta} - 2\min(r_{i\eta}))}\left(1 + \frac{(r'_{ij} - T_d)}{\sum_{j\neq\eta}^{n}(r'_{ij})}\right),$$
$$r'_{ij} = T_d$$

Table 1 compares our scheme with the heuristic resource allocation algorithms. It turns out that the proposed scheme is flexible and lightweight for resource-constrained WoT applications.

Case Study: Web-Based Environmental Monitoring

In the case study, there are four types of sensors to capture the environmental parameters: temperature (degrees Celsius), relative humidity (percent), UV index, and particulate matter up to 2.5 micrometers (PM 2.5) value (μg/m^3). The sensors are deployed in relatively independent subsystems, associating with the corresponding actuators (that is, thermostat, [de]humidifier, anti-ultraviolet, and air purifier).

The prior attention vector $V_{1\times4} = [v_1, v_2, v_3, v_4]$ is determined by a historical prior attention vector set $V_{T\times4} = [v_{m1}, v_{m2}, \ldots, v_{m4}]$ $(m = 1, \ldots, T)$. An objective function $f(V)$ is established to obtain $V_{1\times4} = [0.125, 0.25, 0.25, 0.375]$:

$$f(V) = \sum_{m=1}^{T}\sum_{n=1}^{4}(v_{mn} - v_n)^2.$$

$S_{T\times n}$ is obtained by continuously monitoring the 24-hour sensing data from 30 May through 5 June 2013 in Beijing. Assume that an ideal temperature and relative humidity are 22°C and 50 percent, and the UV index and PM 2.5 value are limited within 2 and 70 μg/m³, which are defined as the criterion. Figure 4 illustrates the data perception and resource allocation, in which Web resources can be regarded as a constant, and dynamic resource proportion is distributed according to the real-time attention arrays. The scheme provides the scalability and stability properties:

- *Scalability.* The attention arrays are time-sensitive variables, and dynamic resource allocation is accordingly realized based on the real-time data perception. A growing amount of sensing data is persistently handled during the interactions, and additional sensors can be extended to provide new functionalities at the minimal effort.
- *Stability.* The sensors are relatively independent, and an accidental breakdown of a sensor will not cause other sensors to be unavailable. The associated actuators share a common Web resource pool, and an emergency resource response can be launched to address an urgent event. Degeneration might occur when the sensors or actuators persistently suffer from overload utilization or malicious abuse, and the threshold control mechanism ensures that an approximately corrupted system will be kept in a safe state to prevent resource exhaustion.

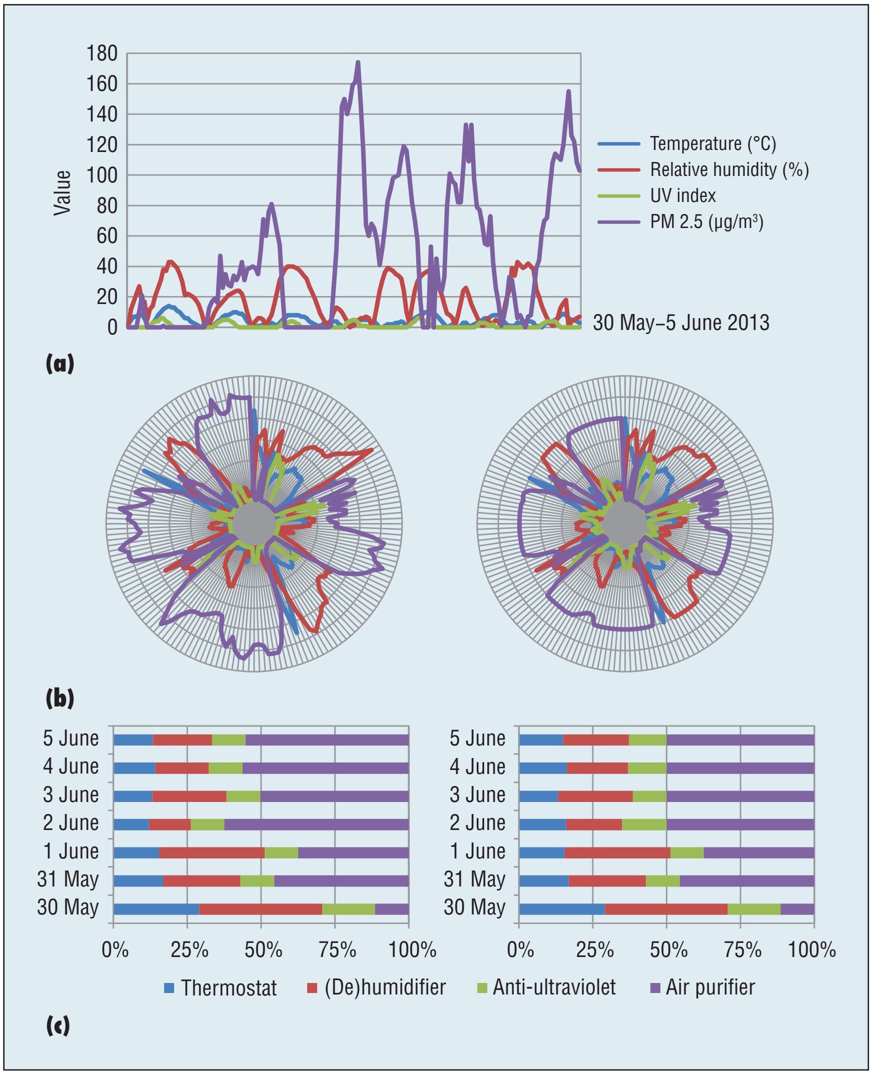

Figure 4. Data perception and resource allocation. (a) The sensing data during one week according to the defined criterion; (b) the original and revised real-time resource allocation; and (c) the original and revised daily resource allocation, in which p = 70 percent, and the threshold T_d = 50 percent.

Resource issues become more noteworthy in the WoT due to the emerging heterogeneous network coexistence and convergence. The WoT resources confront several open challenges including semantic resource description, on-demand resource distribution, spontaneous resource discovery, and cooperative resource sharing. Future WoT resource solutions are expected to be lightweight for providing enhanced efficiency, adaptability, and scalability without compromising quality of service. ■

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