













probabilities, like in [28], with the known problems related to the unavailability of Bayesian posterior probabilities conditions. Therefore, calculating the concept's participation with membership functions of rough sets provides deterministic behavior to the design of a system.

The limitations of the symbiotic partner agent are related with two open issues which refer to the size and the homogeneity of knowledge. The size of the managed knowledge cannot be strictly defined for a general-purpose system. Also, the homogeneity of the concepts participating in the knowledge representation cannot be rigorously defined. However, the internet provides the capability to perform references to well-defined knowledge bases and exemplars reducing the demands for the size of the locally managed memory. In addition, the homogeneity of the concepts participating in the hyperstructure  $\mathfrak{A}$  can be defined with the proper use of the functionalities of intentions and extensions. Therefore, the current limitations of size and concepts of homogeneity can be partially remedied with the use of the internet and the concepts functionality of intentionality and extensionality.

The hyperstructure  $\mathfrak{A}$  supports the development of dynamical hierarchical networks of concepts which can be augmented or reduced using the functionalities of concept intentionality and extensionality. Knowledge is dynamic and capable of offering representations of static snapshots of the instantly holding knowledge, as well as, the knowledge generation [17]. The knowledge generation can be represented by the concept functionalities of intentionality and extensionality which can develop additional concepts, relations augmenting or shrinking the represented knowledge. Therefore, the relational composition of concepts leads to the development of complex concept constructs or newly defined concepts.

The development of concepts networks in the hyperstructure  $\mathfrak{A}$  represent the developing knowledge and provide the capability to discover or extract the contained knowledge. The knowledge extraction can be performed by applying queries on the knowledge graphs or semantic networks consisting of interrelated concepts. In [9], the authors claim that literature information can be turned into knowledge when the received data is placed in a network and new knowledge can be generated by augmenting the network nodes-data-concepts developing extended knowledge graphs. Therefore, knowledge extraction from the concept networks is a technical challenge that can be addressed with Resource Description Framework (RDF), non-

relational databases [9], and language representations of knowledge [18].

Knowledge graphs present similar data structures to networks of concepts and they share analogously practical problems such as the size of the constituting networks with large number of interrelated nodes, the consistency of the denotations of the participating nodes, and the operating environments. In addition, the parameters of each node increase the difficulty of the management administration of concepts networks. However, there are techniques to efficiently traverse the concepts network for searching, placing queries or interacting with questions-answers. In the administration of knowledge graphs besides the developed interrelations among nodes, it is attempted to enrich each node of the formed network with the semantic D codes. Moreover, each code can take up K values forming K-way D-dimensional codes [6] in order to present the similarity among the comparing nodes. Thus, simply traversing the concepts network or applying a query on them, an encoder/decoder model mechanism applies using a discretization / reverse discretization function [26] for representing complex or advanced forms of knowledge. Embedding characteristics is performed in [6] by a function  $F:V \rightarrow R^d$ , where V represents the semantics of concepts placed in a table - vocabulary which corresponds to a vector in  $R^d$  [6]. However, as the size of the concept network is increasing there must be found ways to preserve efficiency and among them compression [6] is considered as promising.

In Denotational Mathematics, with a formally defined environment, the recurrent operations are defined with the big-R notation in the Real-Time Process Algebra (RTPA). Knowledge consisted of concepts networks is represented [35] by the following recurrent expression:

$$\mathfrak{R} \cong R_{k=1}^n \mathfrak{R}^k (\mathfrak{R}^{k-1}) = \mathfrak{R}^n (\mathfrak{R}^{n-1} (\dots \mathfrak{R}^1 (\mathfrak{R}^0))) \quad (9)$$

and base condition as,

$$\mathfrak{R}^0 = X_{l=1}^m C_l \quad (10)$$

where X is the cartesian product among  $C_l$ 's. Denotational Mathematics provides the means to develop knowledge bases [35] with which knowledge can be acquired, fused in the base, manipulated and retrieved. Hence, there is a sound and complete logic environment to administer knowledge bases [35]. However, such knowledge bases develop relationships and references among the concepts over time undergoing a change of its contents due to its interaction with the environment. Thus, the behavior of the formed system of the concepts network is changing according to the built relationships among the concepts expressing the self-adjustment or the

earned experiences from the interaction of the surrounding environment resulting in a cognitive dynamic system [14]. The applying rules of the concept's networks spawn the observed intelligence, learning, adaptivity, activity or action in real-time affected by the surrounding environment [14]. The operation of a system consisting of a knowledge base requires the support of a complete computing environment. Such a computing environment or system must be initialized, the components of the system are properly synchronized and sense internal and external events interrupting the executing flow of operations and re-schedules the operations. The internally carried operations must be managed using temporary and permanent memory banks. Thus, such a system collects operations and builds processes with which the system requests, creates, performs, runs, interrupts, completes, delays, suspends, kills, and dispatches the available sets of operations or processes [32]. Therefore, the operation of a knowledge base requires the support from a Real-Time Operating System to manage the carried internal processes and synchronize the requests from the surrounding environment with a Real-Time Operating System (RTOS+) [32].

## 5 Modelling

The description of the data and information exchanged among the ubiquitous computing participants and the system requires an adequately matching model. A brief description of the model is presented in the following as well as the carried procedures during the performed interactions, and the mathematical expression of the dynamic developing behavior.

A system is formed containing the physical context and the context developed into the supporting computer machine. Within this system there is always a continuous interaction between the two contexts. From the physical context, data is flowing to the computer machine while from the computer context data is actuating and affecting the operational terms of the physical context. The total flow of data between the physical and the computer contexts determines the holding knowledge of the formed system.

The physical context is formed by the activity carried by the artifacts and the users in the computer environment. The activity of the artifacts produces data that is driven to the co-functioning computer. The computer is processing the received data and produces data for the connected transducers to properly affect the artifacts and the users of the physical - environmental context. The computer

receives data and produces data that maintain the level of the developed knowledge of the formed system. Figure-1 depicts the interaction between the environmental-physical and the computer contexts presenting the flows of data between the interacting contexts which is proportional to electromagnetic flux.

The flow of data or data flux is the measurable magnitude to represent the total knowledge which is developed in the interaction between a physical and a computer context. The data flux can be used to describe the induced knowledge to the active system such as that of Figure-1. The exchanged data between the physical and computer context contribute to knowledge components of the formed system. The data flux is the magnitude that is formed by the matching data structures of the physical and computer contexts. In other words, given a set B of data structures representing the physical context projected to the set A of data structures representing the computer context is the data flux which is expressed as  $\Phi = B * A$ . The flux  $\Phi$  represents the number of procedures carried out in a system in order to develop the holding knowledge of that system. Another term borrowed from electromagnetics is the flux density which in our case is the division of contextual data structures over the holding knowledge's data structures. The contextual data structures are driven by the carried procedures which govern the operation of the occurring system.

When there is observed data flux across contexts then there are spawned processes. The spawned processes act analogously to the generation of voltage when a conductor is moving within a magnetic field. The processes can generate additional processes which can be internal or external to the system depending upon the nature of a closed or open system. Flux is changing along time at discrete time intervals expressed as  $\Phi(t) = \Phi(t_1) - \Phi(t_0) = (\Delta\Phi_1(t_1) + \Delta\Phi_2(t_1) + \Delta\Phi_3(t_1) + \dots) - (\Delta\Phi_1(t_0) + \Delta\Phi_2(t_0) + \Delta\Phi_3(t_0) + \dots)$  representing the flux of the constituting knowledge components. Knowledge can be represented as the rate of change of flux given by  $K = \Delta\Phi / \Delta t$ .

## 6 Determination and Formal Definition of Data Flow

The sensed knowledge flow leads to the determination of the dimensionless magnitude of data flux. The static and dynamic aspects of flux are associated with the corresponding aspects of knowledge.



## 6.1 Data Flux

The interaction between the PS and VS spaces is controlled by the intermediate symbiotic partner agent. The interaction between the PS and VS spaces is sensed by the transmission/reception of data which can be performed by the direct connection of each PS or VS space with the symbiotic partner agent or through the use of some intermediate memory bank. The interaction between the PS and VS spaces is verified by the existence of data flow. The enumeration of the set of data structures from the PS space is denoted by  $F_{in}$  while the corresponding set received is denoted as  $F_{out}$ . When data is exchanged between PS and VS spaces then there are two options: (a) data status is changed, and (b) the concept network managed by the symbiotic partner agent is also changed. Thus, we define the magnitude of data flux  $F$  given by

$$F \triangleq \frac{F_{out}}{F_{in}} \quad (11)$$

with  $F_{in}$  being the data transferred from the PS to VS while  $F_{out}$  is the returned data from VS to PS. Thus, at any given instant of time  $t$ , the function  $f(t)$  represents the flux  $F$  which takes values given by

$$f(t) = \begin{cases} < 1, & \text{cardinalities: } |F_{in}| > |F_{out}| \\ = 0, & \text{cardinalities: } |F_{in}| = |F_{out}| \\ > 1, & \text{cardinalities: } |F_{in}| < |F_{out}| \end{cases} \quad (12)$$

The comparisons between the sets of  $F_{in}$  and  $F_{out}$  can be performed at the syntactic or the semantic levels. In any case, the comparison focuses on the magnitude

$$F_t = (F_{in} \cap F_{out}) \quad (13)$$

The instant value of flux  $F_t$  can be given by the symbiotic partner agent which can be analyzed with the application of Denotational Mathematics. The use of Denotational Mathematics facilitates the formal description of the computing environment that supports the operation of the symbiotic partner agent, as well as, the functionality of the symbiotic partner agent itself. The computing environment can be described and implemented with an appropriate modification of the Real-Time Operating System (RTOS+) [32]. In a similar fashion, the formal description of the symbiotic partner agent can be performed with the use of the available tools provided by the Real-Time Process Algebra (RTPA) given in [38].

## 6.2 Static representation of Flux

The representation of the PS and VS spaces can be achieved with the formal description of the existing data structures. Thus, the static representation of the flux is described by the intersection of the sets constituting the fluxes entering and leaving from the

symbiotic partner agent. At a given instance of time, the flux  $F_{out}$  represents how the developing knowledge in the symbiotic agent affects the carried processes in the PS physical domain. Similarly, the flux  $F_{in}$  represents how the developing processes in the physical domain affects the build of knowledge in the symbiotic partner agent. Therefore, the static representation of flux is performed by the description of the data structures existing in the artifacts of the physical domain and the memory of the symbiotic partner agent.

## 6.3 Dynamic representation of Flux

The symbiotic partner agent is the software system that continuously and constantly supports the operation of a ubiquitous computing environment such as UbiHealth. This continuous cooperation and interaction between the symbiotic partner and the UbiHealth environment is driving the development of flux. The presence of flux leads to the development of knowledge which is the result of the changing in the transfer of structured data. The flux is the rate of change of the data exchanged between PS and VS. Therefore, the existence of flux leads to the development of knowledge and hence, the dynamic change of flux is the built knowledge by the symbiotic partner agent.

The knowledge represented by the holding status of the concept networks changes by the received flux. Thus, the state of the concept network changes upon the reception of additional data from the PS space and the governing rules of the concept network bring the network to another state depending upon the previous state. Hence, the concepts network state depends entirely on the previous one revealing a recursive relationship among the states. Moreover, the concept network requires an initialization leading to the conclusion that there must be a supervising real-time operating system that monitors its operation. In addition, the constituting components of the concepts network undergo selectable changes depending upon the reception of flux which can cause only parts of the concepts network to change while others remain unchanged. This fact leads to the conclusion that the concept network operations can be described by recursive partial functions. For instance, the artifacts of a UbiHealth environment can provide sets of data structures that leave the built knowledge unaffected. Therefore, the employment of partial functions provides the advantage of using basic functions which can be closed under complex operations of composition and primitive recursion leading to the following expression:

$$\mathfrak{K}^k = \begin{cases} \mathfrak{K}^0 = c, c \in S_{init} = \{c_1, c_2, \dots, c_n\} \\ \mathfrak{K}^k \mathfrak{K}^{k-1}, & k \in S_{VS} \\ 0, & k \notin S_{VS} \end{cases} \quad (14)$$

The  $\mathfrak{K}^k$  function is a total and computable partial function as it is formed by the collection of partial functions and closed under some fundamental operations for forming new functions from old ones. Therefore, the mathematical representation of the flux is given as a function of the built knowledge: in continuous form

$$F = \frac{dF}{dt} = \frac{d}{dt}(\mathfrak{K}) \quad (15a)$$

or in discrete form

$$F = \Delta F = \Delta(\mathfrak{K}^k - \mathfrak{K}^{k-1}). \quad (15b)$$

## 7 Discussion

The sensed data of the carried processes in the PS space support the built flux that causes the development of the corresponding knowledge in the VS. Any change in the processes' workflow results in an analogous change in flux and consequently, the corresponding effects on the developed knowledge. Thus, flux can be used as that magnitude which senses the functionality of the PS and affects the knowledge of the VS space. Therefore, there always exists a relationship among the processes carried in PS, the developed flux, and the knowledge developing in the VS space.

The carried processes in the PS space and the development of knowledge in the VS space, they are related with direct proportional but not linear relationship. The rate of change of the carried processes provides the rate of change in the developing flux between the PS and VS spaces. In a similar fashion, the given instant of flux causes a definite rate of change in the VS space expressed by the development of knowledge. In other words, flux expresses the dynamic changes in the processes of the PS space and the dynamic changes in the built knowledge, as it is presented in (16) below:

$$F = \frac{d(P_n)}{dt} = \frac{d(K_n)}{dt} \quad (16)$$

where  $P_n$  and  $K_n$  represent the sets of the values domains of the computable functions describing the processes in the PS and the concepts network in the VS spaces respectively.

The engineering design refers to the design of the symbiotic partner agent software which is in between the PS and the VS spaces. The symbiotic partner agent is equipped with adequate modules which are connected with properly defined internet of things (IoT) development in order to sense the functionality of the carried processes in the PS space. The

symbiotic partner agent receives the data structures obtained by the IoT installation in order to develop the built flux. The developed flux feeds the software modules of the symbiotic partner agent in order to develop adequate representations of concepts networks. The functionality of the concept networks adjusts the knowledge status to correspond to the needs of the PS. The changes in the built knowledge feed the decision-making modules of the symbiotic partner agent to react accordingly to the carried processes in the PS space.

The operation of the symbiotic partner agent software interacts with the works, procedures, and processes taking place in the PS space by receiving the produced data. The developing flux passes the flows of data to the symbiotic partner agent to develop the corresponding concepts network. The developing knowledge by the concepts networks feeds the decision-making module to cause the symbiotic partner agent to export the data to those data structures required in order to transfer the knowledge impacts to the carried processes of the PS space. Therefore, knowledge governs the functionalities of the processes operating in the physical domain.

## 8 Conclusion

The formal mathematical representation of knowledge with the application of Denotational Mathematics provide the opportunity to represent constituting elements and quantified magnitudes. The formal Denotational Mathematics framework provide adequate mathematical tools to perform manipulations on the rigorously defined elements, magnitudes and their relationships which are required to express the built knowledge.

Between PS and VS, the developed knowledge is caused by the presence of flux which is defined by the update of the data structures transferred and exchanged between the two spaces. Flux is a magnitude proportional to knowledge and it is used to perform knowledge-able control on the physical domain. The formal mathematical definition of flux provides the capability to use mathematical tools to determine the instant knowledge, the processes status, and the capabilities of the symbiotic partner agent.

The operation of the symbiotic partner agent facilitates the interactions between the PS and VS spaces. The interaction of the symbiotic partner agent with the computing environment, e.g. UbiHealth environment, provides the capability of applying direct knowledge-based control of the carried processes.

The future research plans focus on the development of a symbiotic partner agent prototype. The prototype is expected to provide the basis for experimentation on the uses of flux in the development of knowledge and knowledge-based control on the surrounding computing environments.

The prototype is going to present the attributes mentioned above with the static and dynamic facilities provided by Denotational mathematics. The symbiotic partner agent will be designed as an internet service implementing the quantization of the continuous magnitude of Knowledge Flux along with the relationship with time, i.e. the consideration of knowledge as a function time.

#### References:

- [1] Abowd G.D., Dey A.K., Brown P.J., Davies N., Smith M., & Steggles P. (1999) Towards a Better Understanding of Context and Context-Awareness. In: Gellersen HW. (eds) *Handheld and Ubiquitous Computing*. HUC 1999. Lecture Notes in Computer Science, vol. 1707. Springer, Berlin, Heidelberg.
- [2] Anagnostopoulos, C., A. Tsounis, S. Hadjiefthymiades. (2007). Context awareness in mobile computing environments. *Wireless Personal Communications*, 42 (3), 445-464.
- [3] Armand, A., Filliat, D. & Ibañez-Guzman, J. (2014). Ontology-based context awareness for driving assistance systems. *IEEE Intelligent Vehicles Symposium Proceedings*, Dearborn, MI, USA, pp. 227-233.
- [4] Brickley, D., & Guha, R. (2001). *RDF Vocabulary Description Language 1.0: RDF Schema*. W3C Working Draft. <http://www.w3.org/TR/PR-rdf-schema>
- [5] Bricon-Souf, N., & Newman, C.R. (2007). Context awareness in health care: A review, *International Journal of Medical Informatics*, 76(1), 2-12.
- [6] Chen, T., Min, M.R., & Sun, Y. (2018). Learning k-way d-dimensional discrete codes for compact embedding representations. arXiv preprint arXiv:1806.09464.
- [7] Dalley, J., & Hamilton, B. (2000). Knowledge, context and learning in the small business. *International Small Business Journal*, 18(3), 51-59.
- [8] Dey, A.K., Salber, D., Abowd, G.D. & Futakawa, M. (1999). The Conference Assistant: combining context-awareness with wearable computing. *Digest of Papers. Third International Symposium on Wearable Computers*, San Francisco, CA, USA, 21-28.
- [9] Dörpinghaus, J., Stefan, A., Schultz, B., & Jacobs, M. (2020). Towards context in large scale biomedical knowledge graphs. [Online]. Available: <http://arxiv.org/abs/2001.08392>
- [10] Gandon, F.L., & Sadeh, N.M. (2004). Semantic web technologies to reconcile privacy and context awareness, *Journal of Web Semantics*, 1(3), 241-260.
- [11] Gellersen, H.W., Schmidt, A. & Beigl, M. (2002). Multi-Sensor Context-Awareness in Mobile Devices and Smart Artifacts. *Mobile Networks and Applications* 7, 341–351.
- [12] Ghosh, A., Heffernan, N., & Lan, A. S. (2020). Context-aware attentive knowledge tracing. In *Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, 2330-2339.
- [13] Hofer, T., Schwinger, W., Pichler, M., Leonhartsberger, N., Altmann, J. & Retschitzegger, W. (2003). Context-awareness on mobile devices - the hydrogen approach. *36th Annual Hawaii International Conference on System Sciences*, Big Island, HI, USA, 10-18.
- [14] Kinsner, W. (2007). Towards cognitive machines: Multiscale measures and analysis. *International Journal of Cognitive Informatics and Natural Intelligence*, 1, 28–38.
- [15] Korpipää P., & Mäntyjärvi J. (2003) An Ontology for Mobile Device Sensor-Based Context Awareness. In: Blackburn P., Ghidini C., Turner R.M., Giunchiglia F. (eds) *Modeling and Using Context*. Lecture Notes in Computer Science, 2680. Springer, Berlin, Heidelberg
- [16] Koskinen, K. U., Pihlanto, P., & Vanharanta, H. (2003). Tacit knowledge acquisition and sharing in a project work context. *International journal of project management*, 21(4), 281-290.
- [17] Lieto, A., Lebiere, C. & Oltramari, A. (2018). The knowledge level in cognitive architectures: Current limitations and possible developments, *Cognitive Systems Research*, 48, 39-55.
- [18] Liu, W., Zhou, P., Zhao, Z., Wang, Z., Ju, Q., Deng, H., & Wang, P. (2020). K-BERT: Enabling Language Representation with Knowledge Graph. *Proceedings of the AAAI Conference on Artificial Intelligence*, 34(03),

2901-2908.

<https://doi.org/10.1609/aaai.v34i03.5681>.

- [19] Lukowicz, P., Pentland, S. & Ferscha, A. (2012). From Context Awareness to Socially Aware Computing. *IEEE Pervasive Computing*, 11(1), 32-41. doi: 10.1109/MPRV.2011.82
- [20] Pedrycz W. (2021). From Data to Information Granules: An Environment of Granular Computing. *IEEE 20th Int'l Conf. on Cognitive Informatics and Cognitive Computing (ICCI\*CC'21)*, Banff, AB., Canada, IEEE CS Press, Oct., p.2.
- [21] Pomerol, J.C., & Brézillon P. (2001). About Some Relationships between Knowledge and Context. In: Akman V., Bouquet P., Thomason R., Young R. (eds) *Modeling and Using Context. Lecture Notes in Computer Science*, 2116. Springer, Berlin, Heidelberg.
- [22] Preuveneers, D., & Berbers., Y. (2008). Internet of Things: A Context Awareness Perspective. *The Internet of Things: From RFID to the Next-Generation Pervasive Networked Systems*, Auerbach.
- [23] Randell, C., & Muller, H. (2000) Context awareness by analysing accelerometer data. *Digest of Papers. Fourth International Symposium on Wearable Computers*, Atlanta, GA, USA, 175-176.
- [24] Ranganathan, A., & Campbell, R.H. (2003). An infrastructure for context-awareness based on first order logic. *Personal and Ubiquitous Computing*, 7(6), 353-364.
- [25] Rosemann, M., Recker, J., Flender, C., & Ansell, P. (2006): Understanding Context-Awareness in Business Process Design. *Proc. of the 17th Australasian Conference on Information Systems*. Australia Association for Information, Adelaide, Australia.
- [26] Sachan, M. (2020). Knowledge Graph Embedding Compression. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, 2681-2691.
- [27] Sarivougioukas, J., Vagelatos, A., Parsopoulos, K., & Lagaris, I. (2017). *Home UbiHealth*, Encyclopedia of Information Science and Technology, Fourth Edition, IGI Global.
- [28] Sarivougioukas, J., & Vagelatos, A. (2022). Fused Contextual Data with Threading Technology to Accelerate Processing in Home UbiHealth. *International Journal of Software Science and Computational Intelligence (IJSSCI)*, 14(1), 1-14.
- [29] Yousheng, T., Wang, Y., & Hu, K. (2009). A knowledge representation tool for autonomous machine learning based on concept algebra. In *Transactions on Computational Science V*, 143-160. Springer, Berlin, Heidelberg.
- [30] Wang, Y. (2012). On denotational mathematics foundations for the next generation of computers: cognitive computers for knowledge processing. *J Adv Math Appl* 1(1), 118–129.
- [31] Wang, Y., Ngolah, C., Zeng, G., Sheu., P.C., Chiy, P., & Tian, Y. (2010). The Formal Design Model of a Real-Time Operating System (RTOS+): Conceptual and Architectural Frameworks. *International Journal of Software Science and Computational Intelligence* 2(2), 105-122.
- [32] Wang, Y., Baciú, G., Yao, Y., Kinsner, W., Chan, K., Zhang, B., & Hameroff., S. (2010). Perspectives on cognitive informatics and cognitive computing. *International Journal of Cognitive Informatics and Natural Intelligence*, 4(1), 1-29.
- [33] Wang, Y., Zatarain, O., & Valipou, M. (2017). Building cognitive knowledge bases sharable by humans and cognitive robots. In *2017 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, 3189-3194.
- [34] Wang, Y. (2015). Concept algebra: A denotational mathematics for formal knowledge representation and cognitive robot learning. *Journal of Advanced Mathematics and Applications*. 4(1), 61-86.
- [35] Wang, Y. (2014). On a novel cognitive knowledge base (CKB) for cognitive robots and machine learning. *International Journal of Software Science and Computational Intelligence*. 6(2), 41-62.
- [36] Wang, Y. (2008). On concept algebra: A denotational mathematical structure for knowledge and software modeling." *International Journal of Cognitive Informatics and Natural Intelligence*. 2(2), 1-19.
- [37] Wang, Y. (2007). The OAR model of neural informatics for internal knowledge representation in the brain. *International Journal of Cognitive Informatics and Natural Intelligence*. 1(3), 66-77.

- [38] Wang, Y. (2009). Toward a formal knowledge system theory and its cognitive informatics foundations. In Transactions on Computational Science V, 1-19. Springer, Berlin, Heidelberg.
- [39] Wang Y., Karray F., Kaynak O., Kwong S., Leung H., Plataniotis K.N., Hou M., Rudas I.J., Tunstel E., Trajkovic L., and Kacprzyk J. (2021), Perspectives on the Philosophical, Cognitive and Mathematical Foundations of Symbiotic Autonomous Systems (SAS), *Philosophical Transactions of Royal Society (A)*, 379(x):1-16, Oxford, UK.
- [40] Wang Y., Hou M., Plataniotis K.N., Kwong S., Leung H., Tunstel E., Rudas I.J., and Trajkovic L. (2021), Towards a Theoretical Framework of Autonomous Systems Underpinned by Intelligence and Systems Sciences, *IEEE/CAS Journal of Automatica Sinica*, 8(1), 52-63.
- [41] Weiser, M. (1999). The computer for the 21st century. *ACM Mobile Computing and Communications Review*, 3(3), 3-11.