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Memristor as an archetype of dynamic data-driven systems and applications to sensor networks

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Abstract

Since its introduction a decade ago, DDDAS has been applied to a wide range of science and technology fields, with specific focus of areas requiring fast and reliable processing of massive data streams from diverse resources. It is crucial to explore architectures and systems which are naturally suited to the DDDAS framework. In this paper, we show that the memristor – the fourth fundamental two-terminal passive circuit element alongside the well-known resistor, capacitor, and inductor – affords the efficient implementation of the working principles of DDDAS. Hence memristors can be considered as an archetype of DDDAS nanoscale hardware embodiment, being the smallest and most basic dynamic data driven application system. Memristors are electrical components with inherent memory processes; they have been predicted about four decade ago and have been physically implemented recently. We discuss the role that DDDAS may play in the development of computing platforms and sensor networks based on memristors in the next few years.

Keywords: DDDAS, Memristor, Sensor Networks

1. Introduction

Dynamic data driven application system (DDDAS) has been introduced as a general paradigm to incorporate additional data into an executing application and, at the same time, allow the application to dynamically adapt to the incoming data flow. Since its introduction, DDDAS has been employed in numerous contexts, especially in problems involving large-scale networks, such as supply-chain, energy infrastructure, transportation [1] with massive amount of data streams [2]. Important examples of DDDAS are advanced measurement and instrumentation in adaptive sensor networks. An autonomous sensor network is a collection of sensor nodes with limited processing, power, and communication capabilities that monitor a real world environment through differing modalities. The nodes gather information about the local environment, preprocess the data, and transmit the output to other nodes. Using intelligent framework design, the network can support decision making and realize complex tasks. As a matter of fact, this interactive and adaptive sensor system are an example of Dynamic Data Driven Applications Systems.

All these scenarios refer to large-scale systems. At the same time, it is interesting to consider potential components of such systems and study how they exhibit the basic properties of DDDAS paradigm. In this paper, we discuss the possibility for the memristor [3], the fourth fundamental two-terminal passive circuit element, to be considered as an archetype of DDDAS at a small scale, since the current technologies allow it to be manufactured at nanoscale. The memristor has the characteristics of a non-linear resistor with memory, in the sense that its resistance is a function of the charge that has flowed through the device and its practical significance became evident in 2008 when HP

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made public its work [4], which attracted the attention of the scientific community. Such capabilities entail dynamic integration of the computational and measurement aspects of an application in a dynamic feed-back-loop.

The present paper is structured as follows: first, we describe the basic features of memristor and its working principles; then, we provide basic basic examples of how memristor could be studied in the framework of DDDAS; last, we outline the perspectives of integrating memristor-based systems into large-scale sensor networks.

2. Fundaments of memristor

The memristor was introduced through an 'axiomatic approach' [3] which defines four *fundamental* circuit variables – voltage v, current i, charge q, and flux ϕ – and describes the two-terminal circuit elements as relationships between two of the four variables. There are six independent permutations of two objects in a bank of four, and hence there must be six ways to link v, i, q, ϕ: two of them correspond to the definitions of current (Eq. 1) and the Faraday's law (Eq. 2) whereas the other three correspond to the canonical circuit elements (Eqs. 3, 4, and 5). For the sake of completeness, Eq. 6 has to correspond to a fourth fundamental two-terminal circuit element: the memristor.

$$\text{Definition of current:} \quad dq = idt \tag{1}$$
$$\text{Definition of voltage:} \quad d\phi = vdt \tag{2}$$
$$\text{Resistor:} \quad dv = Rdi \tag{3}$$
$$\text{Capacitor:} \quad dq = Cdv \tag{4}$$
$$\text{Inductor:} \quad d\phi = Ldi \tag{5}$$
$$\text{Memristor:} \quad d\phi = Mdq \tag{6}$$

From this equation, it is clear that when the memristance M is not a function of q, the memristor behaves like a resistor. Since the memristance M depends on the charge, the element retains a memory of the past events of the input current. It is possible to prove [5] that all devices are characterized by the fact of displaying a pinched hysteresis loop in the current-voltage characteristic, as shown in Fig. 1, are memristors, and vice versa.

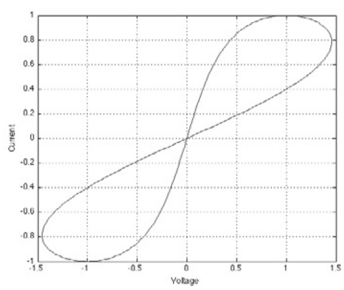

Figure 1: A pinched hysteresis loop in the current-voltage characteristic is the hallmark of memristors.

The working principles of the memristor can be better understood through an analogy with mechanical devices proposed in [6] and [7], and reported in Fig. 2. This device is composed of a dashpot cylinder with a tapered friction rod attached at a certain distance from the dashpot enclosure and a piston to which is attached a thick rubber disc. The diameter of flexible rubber sleeve varies with the penetration of the piston d and hence the force needed to push the piston further is a function of d. In other words, the incremental resistance depends on the instantaneous piston displacement. This situation is analogue to the one of a resistor whose resistance depends on the charge flown, as it can be easily found by integrating Eq. (6) over time. It is then reasonable to model the dashpot-piston system as a memristor [6].

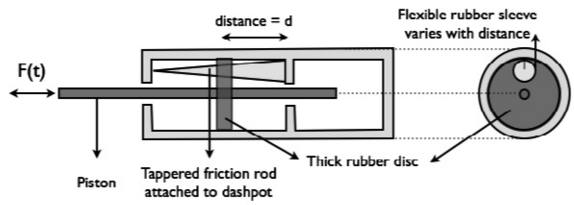

Figure 2: Mechanical equivalent of a memristor.

3. A DDDAS perspective of memristor

From the description above, it is evident that in general the memristor can be described as a basic circuit element that adapts to the continuos flow of data. This characteristic, among others, indicate that the memristor may be a breakthrough in the field of artificial intelligence [8]. Memristors can model basic neurophysiological processes including the sodium-potassium pumps in a very efficient way; memristive devices on the nanoscale can implement models of synapsis and in this way realize neuromorphic systems [9]. Recent research about the fabrication of memristive crossbar structures support these claims [10] (see Fig. 3). This implies that the memristor may soon become a

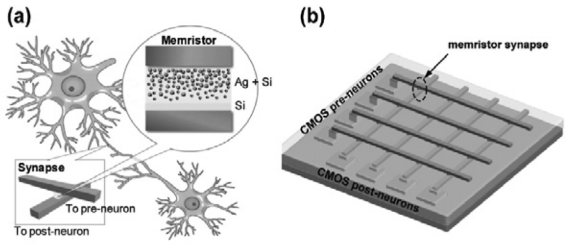

Figure 3: Schematic illustration of the potential link between memristor and synapses: (a) illustration of synaptic connection; (b) memristor crossbar structure [10].

key element to implement genuine biologically-inspired systems composed of myriads of simple elements that weakly interact to produce a coherent, goal-oriented behavior at the level of the overall network. At a much larger scale, these properties are sought by DDDAS. Therefore, it is expected that the experience gained from memristive technology can be used to advance full-scale DDDAS, including intelligent sensor systems and distributed data processing.

4. Discussion and Conclusions

4.1. The role of memristor in decision support based on DDDAS

Memristors are expected to find a quick application in a broad range of fields, both defense and civilian, which need a continuously adaptive computational platform. In rapidly changing, dynamic scenarios, seamless interoperability of components of distributed systems is imperative to achieve reliable assessment of the operational environment to support strategic decision-making. Specific constraints include limitations in time and resources imposed by the unpredictable events. Due to the complexity of the operation, this requires multi-sensor fusion of often contradictory pieces of information. Data are processed from high-dimensional, heterogeneous sensor resources, coming from multiple platforms. Decisions must be made between various potential scenarios. Knowledge-based systems are critical for robust decision making. Decision entities that are more knowledgeable will be able to approach problems in ways that less knowledgeable entities cannot. Moreover, decision-making processes no longer need focus on the passive oriented approaches, rather they can focus instead on being proactive and agile [11].

DDDAS techniques include data acquisition, pattern recognition and classification, data fusion from multi-modal sensors, mobile platforms navigation and control in hostile environment, and the reliable detection and characterization of events [12]. Distributed decision support systems are in high demand in a wide range of application areas where massive streams of data from diverse sources must be rapidly combined to support rapid response and control. It is especially challenging to develop systems capable of continuously adapting the decisions in complex and changing conditions in the monitored system and in its environment. Lessons learned from human cognitive processing can be very beneficial in developing decision support systems, to improve their reliability and speed of operation.

4.2. Example of network-centric scenario

Net-centric approach to information fusion is an excellent example of a field which can benefit from our ideas in DDDAS. Net-centric approach emphasizes the interaction and complementary aspects of the components of a monitoring and surveillance system, as opposed to the fragmented nature of the operation resulting from a more traditional, platform-centric model. There is clear evidence of the benefits from heightened situational awareness and real-time response in net-centric operations. In future battle spaces, vast numbers of sensors and unmanned vehicles will be in simultaneous use, each with different sensing capabilities providing disparate views of the operations [11] [12]. Networked operations indicate a drastic change from passive, reactive data collections to proactive, anticipating mode of sensing. Mission-oriented active sensing provides the user with actionable information, which has a specific meaning in the context of its specific task and increases its situational awareness. Interconnected agents with increased situational awareness are able to coordinate their operation for more efficient collective effect. The main characteristics of network centric approach are summarized in Fig. 4 [11], which includes three major domains of the warfare: physical, information, and cognitive. The intersection of physical and information domain signifies the speed and access of the employed force, and this reflects a traditional view on operations. By considering the cognitive domain as a key aspect of warfare, additional important components can be identified. At the interlay of cognitive and physical domains lies the deployment and operation of the weaponry by the fighter. Finally, considering the interface of cognitive and information domains, the meaning of the obtained sensory information comes into play and its relevance to the mission command. Net-centric warfare includes all three major aspects, requiring simultaneous processing of multiple streams of diverse data.

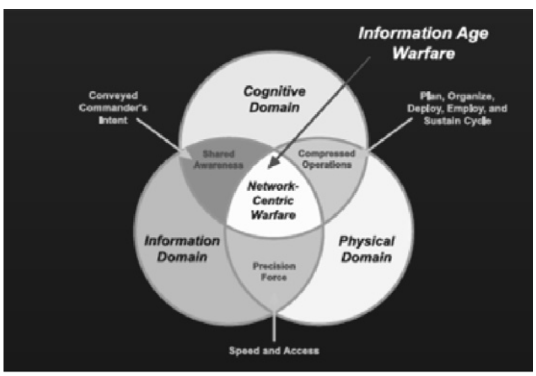

Figure 4: Conceptual view of major components of the net-centric operation paradigm, in a warfare scenario [11].

Figure 5 shows an example of net-centric approach in the case of networks of autonomous sensor agents. In general we have N agents, each of which has its dedicated inputs and corresponding low-level task. The system has the following components:

- Preprocessor: Input compression, normalization, units $B1, B2, \ldots, BN$.
- Classifier: Identification/recognition of data, $C1, C2, \ldots, CN$;
- Comparator: Low-level decision making, $D1, D2, \ldots, DN$;

- Controller: Achieve dynamical (chaotic) balance, $E1$, $E2$, ..., EN;
- Extractor of common modes (EC): Detect covariant oscillations in separate KIII sets.

The preprocessor, classifier, comparator, and controller modules perform tasks belonging to the individual agents. The extractor module (EC) is privileged with connections to all N agents through connection to the comparator units. EC has a crucial high-level function (KIV), i.e., it extracts the coherent components from the individual agents. The coherent component can be very small, typically $< 1\%$. However, this small covariant fraction of the signals indicates the high-level interaction in the network. EC makes the decision based on the covariant component, as it is manifested through the intermittent phase transitions [13].

The defining feature of the multi-layer sensor fusion and decision support is the high-level operation of constructing an image of a future state of itself in relation to its environment and its goal. The system generates nested frames of actions to be taken step-by-step, as well as serial predictions of the frames of multi-sensory inputs. Its advance in each serial step is conditional on conformance of predicted and actual frames within the limits of abstraction and generalization. Past experiences are stored in the connectivity matrices of the component layers. These matrices store the perceptual consequences of the intentional actions taken earlier, which constitute all what the agent can 'know' about the environment. The resulting sensory fusion approach serves as a prototype of future cognitively-motivated decision support systems.

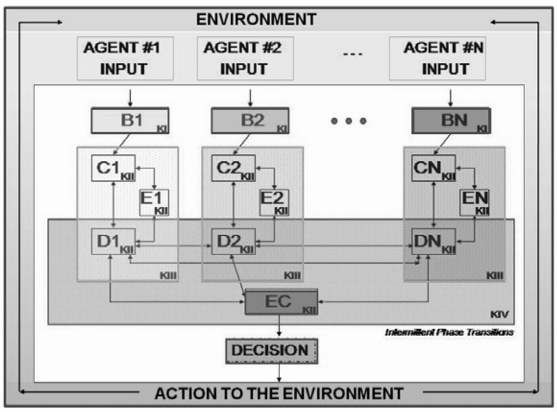

Figure 5: Schematic view of the decision making algorithm in the network of N agents. The notations in the case of the i-th agent are: Bi preprocessor, Ci classifier, Di comparator, Ei controller. EC denotes the entorhinal cortex model, which performs the overall decision-making. Bi unit is a KI set; Ci, Di, Ei, are KII sets and together they comprise the i-th $KIII$ set. The EC in cooperation with the $D1$, $D2$, , DN sets represents the high-level KIV behavior with intermittent phase transitions.

4.3. Conclusions and future perspectives

In an environment subject to sudden changes data must be processed from high-dimensional, heterogeneous sensor resources, and multiple platforms. In this scenario, decision support based on DDDAS may provide a quick and effective response. Due to the complexity of the operation, this requires integration of often contradictory information. In this paper, we outlined the basic principles of memristive systems, which can be seen as a basic component for DDDAS. We also presented an example of network-centric approaches, which shape advanced command and control approaches. Our approach develops a novel memristor-based decision support system, by which information is not passively received but actively predicted and anticipated. Assigned goals and guidelines serve as constraints in the knowledge-base available a priori for the system. The adaptive memristor-based mechanism can serve as an essential component to implement DDDAS, and it helps to interpret and understand the observed data.

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