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Collective hybrid intelligence: towards a conceptual framework

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Abstract

Purpose – Human or machine, which one is more intelligent and powerful for performing computing and processing tasks? Over the years, researchers and scientists have spent significant amounts of money and effort to answer this question. Nonetheless, despite some outstanding achievements, replacing humans in the intellectual tasks is not yet a reality. Instead, to compensate for the weakness of machines in some (mostly cognitive) tasks, the idea of putting human in the loop has been introduced and widely accepted. In this paper, the notion of collective hybrid intelligence as a new computing framework and comprehensive.

Design/methodology/approach – According to the extensive acceptance and efficiency of crowdsourcing, hybrid intelligence and distributed computing concepts, the authors have come up with the (complementary) idea of collective hybrid intelligence. In this regard, besides providing a brief review of the efforts made in the related contexts, conceptual foundations and building blocks of the proposed framework are delineated. Moreover, some discussion on architectural and realization issues are presented.

Findings – The paper describes the conceptual architecture, workflow and schematic representation of a new hybrid computing concept. Moreover, by introducing three sample scenarios, its benefits, requirements, practical roadmap and architectural notes are explained.

Originality/value – The major contribution of this work is introducing the conceptual foundations to combine and integrate collective intelligence of humans and machines to achieve higher efficiency and (computing) performance. To the best of the authors' knowledge, this the first study in which such a blessing integration is considered. Therefore, it is believed that the proposed computing concept could inspire researchers toward realizing such unprecedented possibilities in practical and theoretical contexts.

Keywords Crowdsourcing, Human computation, Autonomous control, Collective machine intelligence, Human–machine collaboration, Hybrid intelligence

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1. Introduction

The concept of computation has evolved over the years with respect to real-world requirements and technological advancements (Mahoney, 1988; Copeland, 2000). In this regard, many computing paradigms have been introduced so far, such as Kephart and Chess (2003), Bargiela and Pedrycz (2016); and Shi *et al.* (2016). In addition to the infrastructural necessities of any computing process, an old dream in this context is the realization of full autonomy in computing, decision making and similar intellectual processes. Achieving this level of automation, in essence, needs to add intelligence to the process in some way. In other words, to be able to come up with (super) human-level decisions, an autonomous (computing/control) system should be equipped with adequate infrastructural facilities, computing power and intelligence (Feigenbaum, 2003; Nilsson, 2005; Cassimatis, 2006).

Nowadays, thanks to the availability of powerful hardware, advanced processing components, inexpensive data storage equipment, sophisticated algorithms and so on, the major challenge in achieving such dreamy machines is the lack of sufficient human-level intelligence. Although many efforts have been spent in this direction (Decker, 2000; Hibbard, 2001; Zadeh, 2008; Bundy, 2017), replacing human intelligence by machines' has not yet been realized literally. On the other side, leveraging humans' brainpower to improve machines' performance has become an efficient approach during recent years (Weyer *et al.*, 2015; Ofli *et al.*, 2016; Chang *et al.*, 2017). Therefore, one may think that instead of trying to build machines to take the place of humans, it would be better to establish a foundation to facilitate joint work of humans and machines to tackle large-scale problems. Although hybrid intelligence paradigm introduces some opportunities to take benefits of human and machine intelligence (Huang *et al.*, 2017), lack of a reference model/general architecture to adhere to its principles causes some non-uniformity. Moreover, adhering to this approach may not warrant taking advantages of available possibilities. On the other side, volunteer computing (Beberg *et al.*, 2009) as an interesting and working idea mainly focuses on leveraging computing resources of the participants, e.g. their PCs and browsers (Fabisiak and Danilecki, 2017).

One can apparently observe that despite the huge available opportunities to synthesize various capabilities of humans and machines, absence of a comprehensive approach to make the most of them is an obvious drawback. In other words, any framework/mechanism which could integrate intelligence and computational resources of human agents and machine entities in different levels could come up with the best of both worlds. In this respect, with the aim of studying previous efforts and current status of similar researches, a brief overview is conducted. Then, to take the efficiency of such human–machine cooperation and collaboration to an unprecedented level, the conceptual architecture of a new evolutionary computing/automation framework, entitled collective hybrid intelligence (CHI), is proposed and its related issues and considerations are discussed in detail. According to the current findings and achievements as the building blocks of the introduced solution, it is expected that the proposed concept could extend borders of the researches in the field to increase efficacy of human–machine synergy in performing computing tasks.

The rest of this paper is organized as follows. At first, an overview of the context and intention of the paper is provided in Section 2. The background and preliminary concepts are briefly overviewed in section 3. The concept of Collective Hybrid Intelligence, its fundamentals, benefits, challenges and realization models are discussed in Section 4. Finally, to clearly describe and discuss how typical systems of this kind (that is constructed based on the proposed framework of CHI) may work in different application domains, three example scenarios are delineated in Section 5.

2. Big picture

Undoubtedly, computers – i.e. smart/intelligent machines – are among the most important and influential inventions of the modern era. Their ever-increasing capabilities in handling a wide variety of computational problems have made computers the artificial superheroes of all times. Over the years and with thanks to the outstanding progress in hardware technology, computing paradigms, machine learning and artificial intelligence, the machines have received an overestimated (and even exaggerated) applause. Affected by science-fiction stories and movies, the public though may be concerned of an early domination of machines over human race. In this regard, defeating the world chess champion by a computer (i.e. IBM's Deep Blue) in 1997[1] and beating a professional Go player by DeepMind's AlphaGo in 2015[2] were convincing evidences for robophobics to conclude that machines finally win over humans and they will be coronated in the near future.

Despite many advancements, the truth is that even latest machines are not jack of all trades and there are many battlefields in which humans can defeat a billion bucks machine[3]. In other words, when it comes to cognitive and intelligent tasks, current machines are not stronger than humans at all (for some example, see Fleuret *et al.*, 2011; Stabinger *et al.*, 2016; Dodge and Karam, 2017). Such facts have driven the research community to rethink the computational paradigms by putting humans in the loop.

In addition to compensate the machine's weaknesses in some ways, human agents could provide human-level training data for machine learning purposes (Zhong *et al.*, 2015; Yang *et al.*, 2018). Because of effectiveness of such cooperation, the (mostly fictional) war between humans and machines has turned into a synergistic collaboration. However, this is not the final destination for the long journey of achieving super intelligence and computational capabilities.

The authors believe that the last step before realization of super human intelligence (or artificial super intelligence) is to make the most of current neglected potentiality that humans and machines can present in a cooperative way. In the rest of the paper, roles of both parties as the building blocks of a new comprehensive computational concept, entitled Collective Hybrid Intelligence, are investigated. As concluding remark, throughout the paper the term machine refers to any non-human and intelligent entity including computers, programs, robots, etc.

3. Background

3.1 Collective human intelligence

Human is an integral part of any computing process; however, over the years his role, position and responsibilities have been changed and evolved. User, operator, supervisor and collaborator are main categories that could reflect humans' role in such processes (Folds, 2016), "For thousands of years, humans' intelligence, problem solving and reasoning abilities presented numerous game-changing ideas and inventions to make the life easier (Sarathy, 2018). Nonetheless, handling sophisticated and complicated situations and issues needed something more than a genius or intelligent decision-maker. Such a fact probably was sparked the motivation to establish the first councils and organized group decision-making bureaus (Burnstein and Berbaum, 1983; Maoz, 1990; Zanakis *et al.*, 2003; Buchanan and O'Connell, 2006).

In the age of computers, for years humans were mostly consumers while a minority group of supervisors were in charge of keeping the machines up and running. In fact, those days can pessimistically be referred to as human-independent computing or machine-driven computing era. Fortunately, many things have changed forever by introduction of crowdsourcing concept (Howe, 2006). The underlying idea of this revolutionary paradigm was taking advantages of humans' collective abilities and efforts to provide more efficient performance. Thanks to its potentials, the initial concept has been soon after widely accepted and evolved into a working decision making and problem-solving strategy (Brabham, 2008; Guazzini *et al.*, 2015; Yu *et al.*, 2018). Although the idea was not an essentially new one[4]; its formulation and attitudes towards leveraging wisdom of crowds and collective human intelligence to cope with problems have made it a popular approach. Based upon the preliminary idea, several computing concepts such as human computation (Von Ahn, 2008), social computing (Wang *et al.*, 2007) and community intelligence (Luo *et al.*, 2009) have been introduced.

Within the recent decade, putting the human in the loop of computing, decision-making (Chiu *et al.*, 2014), ideation (Huang *et al.*, 2014; Schemmann *et al.*, 2016) and similar processes have gained momentum so that one can witness a wide variety of application domains that taking benefits of humans' intelligence and problem-solving potentials. Nonetheless, there is not any serious intention to completely replace machines with humans because this is impossible at all. Instead, the major goal of human-based computation is to compensate machines' deficiency in performing some specific tasks and processes including cognitive and intelligence-intensive ones (Wightman, 2010; Quinn and Bederson, 2011). For example, outsourcing image labeling tasks to the people can provide more accurate efficient and in some cases less-expensive results than relying on machines (Nowak and Rüger, 2010).

In other words, when it comes to the situation in which human-level intelligence is needed, regarding the current machines' state, recruiting human participant is the silver bullet. Further, one can expect more insightful and elaborated answers through involving experts in the form of expert crowdsourcing (Retelny *et al.*, 2014) (Figure 1). Such benefits, by the way, will not come without cost because employment and management of a remarkable number of users in crowdsourcing projects can be a pain in the neck.

Therefore, there is need for elaborated and reliable infrastructure, managerial supervision and workflows. The good news in this context is that availability of technological support and platforms such as Amazon Mechanical Turk (AMT)[5], TurkPrime (Litman *et al.*, 2017) and Figure-Eight[6] (formerly Crowdflower) have made conducting a crowdsourcing campaign as simple as posting a blog.

3.2 Collective machine intelligence

Speaking about artificial intelligence, one of the first things will prompt in the mind is science-fiction movies. Despite the remarkable advancements in the field (Dai and Weld, 2011;

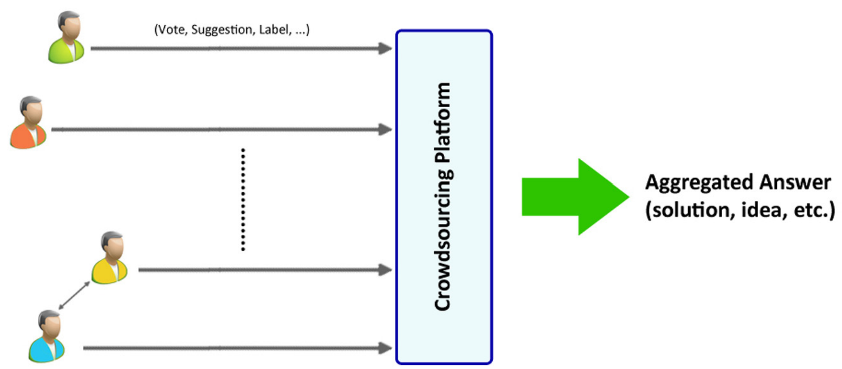

Figure 1.
Simplified schematic of CHI workflow

Pan, 2016; Makridakis, 2017; Lu *et al.*, 2018; Li *et al.*, 2018) and predictions concerned about future of AI (Del Prado, 2015; Müller and Bostrom, 2016; Russell, 2017), there is a long unpaved way to the age of predomination of machines which are capable of controlling everything.

Therefore, one should not be concerned of becoming slave or even agent of an artificial entity in the near future. Things are far different in the real world and (perhaps) the major issue in the field is how to make the most of machines to be more useful and efficient. From a general point of view, machine intelligence can be interpreted as capabilities of machines in handling and performing computational and processing tasks as well as decision making in a more accurate, accelerated and effective way than humans.

Needless to say that coming up with a universal and comprehensive definition of machine intelligence is a controversial and interdisciplinary issue and out of scope of this paper. Anyway, following studies can provide some useful information in this regard (Hernández-Orallo and Minaya-Collado, 1998; Bien, *et al.*, 2002; Legg and Hutter, 2007; Dobrev, 2012).

As mentioned earlier, however, in some cases – including cognitive tasks – machines could not even present human-level performance (Fleuret *et al.*, 2011; Stabinger *et al.*, 2016; Dodge and Karam, 2017); there are many scenarios (such as huge computation, high-volume data analysis, real-time knowledge-based decision making and so on) that may not be realized without help of them. Such outstanding achievements are owing to many years of research and development in machine learning and artificial intelligence as well as advancements in hardware technology and communication/computation infrastructures.

All these facilities and progresses, though, could not quench humans' thirst of creating comprehensive and polymath machines. The ultimate intention in the field is to realize the idea of universal AI (Everitt and Hutter, 2018) or Artificial General Intelligence (Gurkaynak *et al.*, 2016) rather than case-specific ones, e.g. Artificial Narrow Intelligence (Gurkaynak *et al.*, 2016). Achieving such level of autonomy and intelligence, of course, is not practically impossible; however a great deal of (multidimensional) intelligence and resources are needed.

Looking for such an ambitious vision asserts that the days of kingdom of independent and single-dimension artificial intelligence are gone (or will be gone soon) (Wiedermann, 2012; Yampolskiy, 2015; Miailhe and Hodes, 2017). This ongoing revolution borrowed the idea from humans who could think and operate more effectively when being organized in the form of a crowd (Bonabeau, 2009; Leimeister, 2010). The adoption of the concept of collective human intelligence in the context of machines known as collective machine intelligence (Halmes, 2013), wisdom of artificial crowds (Yampolskiy and El-Barkouky, 2011), collective robot intelligence (Kube and Zhang, 1992), etc. (Figure 2).

Regardless of differences in nomenclature and (even) details, the goal is almost a similar and identical one: aggregation and integration of independent (homogeneous/heterogeneous) machines' intelligence, power and resources to produce more effective and efficient outputs. Seems to be partially similar to swarm intelligence (Kennedy, 2006), cluster computing (Sadashiv and Kumar, 2011) and so on, collective machine intelligence (CMI) is a comprehensive and multipurpose concept aimed at taking advantages of (almost) every aspects of a single machine to improve the team performance.

Moreover, in such multi-agent systems the ultimate intention is facilitating collaborative learning, knowledge, experience and resource sharing (Gifford, 2009). Clearly, the core concept of CMI is synergy and all-out cooperation. One of the very early well-experienced realization of the concept is SETI@home project in which millions of computers all over the world contributed in search for the extraterrestrial intelligence through analyzing radio

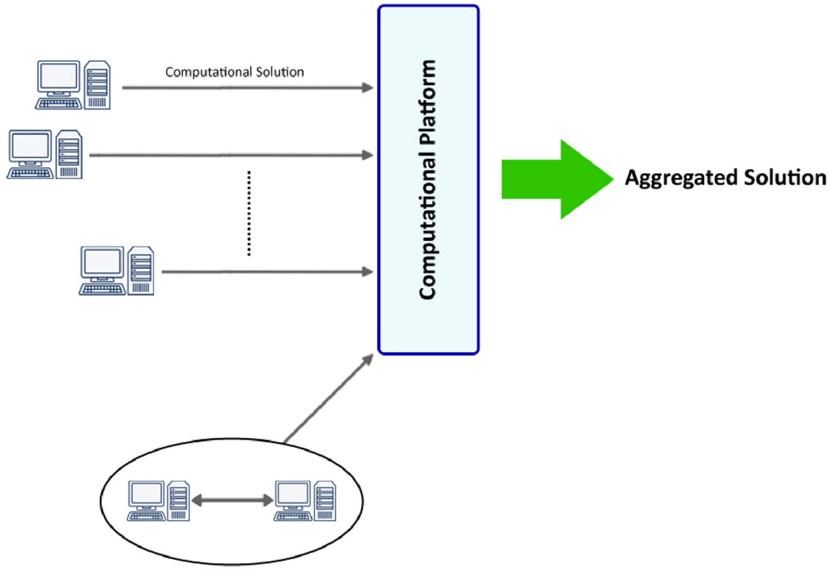

Figure 2.
Simplified schematic of CMI workflow

signals (Anderson, *et al.*, 2002). Although the major goal of the project was compensating the lack of adequate processing resources rather establishing a platform to aggregate independent machine's intelligence; it could be an inspirational case study to prove the applicability of such a strategy.

Further, several remarkable research works have been conducted to empirically study the efficiency of teaming up machines to benefit more of their aggregated utilization, such as projects reported in (Chien *et al.*, 2003; Larson *et al.*, 2009; Pedreira and Grigoras, 2017). Of course, there is still a notable challenge that, e.g. a cluster of powerful machines may face severe difficulties to handle it, namely lack of human-level, cognitive intelligence.

3.3 Hybrid intelligence

The major untouchable difference between humans and most powerful artificial intelligence is the humanity. Thinking, understanding, learning, recognizing and judging like what humans do are the essential barriers that no artificial human-made creature (i.e. machine) could yet overcome them[7][8][9]. Regarding this fact, behind every successful machine, there is a least one human that is in charge of supervising, training or collaborating with it (Folds, 2016).

Emphasizing on the intellectual aspects of such constructive symbiosis, it is referred to as hybrid intelligence (Kamar, 2016). Taking a closer look at the literature reveals there are cases in which the term (hybrid intelligence) was used to point out to other concepts, especially collective machine intelligence, e.g. research conducted in (Deng *et al.*, 2012). In other words, in those instances applying various machine learning algorithms to perform same task in a more efficient way interpreted as leveraging hybrid intelligence. Such an appellation, by the way, may not be completely wrong and irrelevant; though, according to the aforementioned concepts and principles, the term collective machine intelligence can better reflect the underlying concept of interest.

Whether clearly stated or not, when it comes to supporting machine learning algorithms with human intelligence (usually in the form of crowdsourcing), the hybrid intelligence is leveraged (Vaughan, 2017; Nushi *et al.*, 2018; Klumpp *et al.*, 2019) (Figure 3).

One can witness best practices of following this strategy in the field of robotics (Chang, *et al.*, 2017) and particularly for human-robot interaction purposes (Breazeal *et al.*, 2013). Such an approach – at the simplest scenario- can be simulated by training an image processing algorithm with human-labeled images (data sets) (Vaughan, 2017). Among various advantages of incorporating human intelligence in the machine learning workflow (Barbier *et al.*, 2012; Vaughan, 2017; Verhulst, 2018), the followings can be enumerated:

- simplifying problems and making them machine-understandable;
- compensating machines' weaknesses and inefficiency, especially for cognitive tasks;
- facilitating and optimizing learning process; and
- saving costs and time.

Mapping general problems into computational ones and making them machine-readable and –understandable are of hard-to-tackle challenges. Equipping machines with general intelligence – if possible at this time- may not be economical in every case and demands a great deal of efforts and resources with no guarantee of being efficient. Specifically, when it comes to cognitive and human-specific issues, machines face extremely sophisticated challenges. Therefore, taking advantages of humans' intelligence and problem solving power could be considered as the silver bullet. In spite of many advantages hybrid intelligence can present, there is also room for further improvement by mobilizing all the possibilities for great, unprecedented breakthroughs.

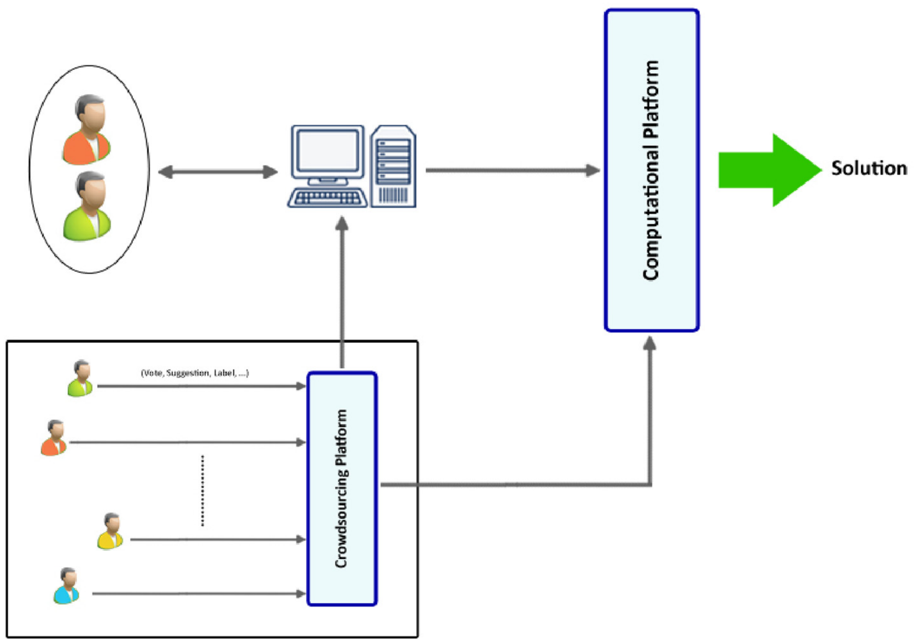

Figure 3.
Simplified schematic of hybrid intelligence workflow

3.4 Discussion (Are these enough?)

To be or not to be? To answer this question about the need for another intelligence-oriented computing concept, the first and foremost is evaluation of the current state progress and challenges. From a high level perspective, computing tasks and processes – based on the contextual and intrinsic requirements- can be categorized into two major classes: intelligence-intensive and resource-intensive. The former refers to the tasks that require some type of cognitive-based judgments, intelligent decision-making, computational intelligence and similar soft (and mostly human-specific) abilities (Maleszka and Nguyen, 2015; Chen and Shen, 2019). On the other side, the latter ones are of time- and power-consuming tasks which introduce dealing with large amount of data (Liu *et al.*, 2015; Jonathan *et al.*, 2017) and high computational and processing requirements (Ilyashenko *et al.*, 2017; 2019; Singh *et al.*, 2019). Natural language processing, semantic-based processing, concept understanding and interpretation are some general intelligence-intensive tasks, while multi-dimensional information processing, big data analysis, high volume communication control and management are among resource-intensive challenges. Notwithstanding the wide variety of real-world needs and requirements, numerous computational processes with different levels of complexity could be introduced.

Therefore, to efficiently handle such situations, the most appropriate computing concept should be used. As an overview on the previously mentioned concepts, their features are summarized and compared in the following table (Table I).

As noted in the Table I, there are some essential issues with current computational paradigms such as scalability and insufficiency to deal with complicated, hybrid tasks that require both enormous intelligence and resources. For example, assume a series of very large-scale semantic and cognitive image and video processing tasks that should provide real-time outputs as well as presenting reliable continuous performance.

As we know, none of the described computational solutions could properly cope with these challenges and being satisfied with the current available solutions is, in fact, a case of any port in a storm. In this regard, it seems necessary to take advantages of current infrastructures and facilities in a novel arrangement for dealing with ever-growing computational requirements.

4. A new human–machine cooperation framework

The availability of human participants, computing resources and software platforms as building blocks of any computational process have facilitated ambitious perspectives. Clearly, we are facing an unprecedented presence and distribution of tangled intelligence and computing power that have partially been overlooked and remained unused.

At the lowest level, a very large, active and interested community of intelligent participants who equipped with the state-of-the-art smartphones are yet to be recruited.

Strategy	Context	Major challenges	Major drawbacks
CHI	Intelligence-intensive tasks	User management, incentive mechanism design	Scalability, non-real time response, limited types of tasks
CMI	Resource-intensive tasks	Implementation, cooperation management, task allocation	Lack of standard interaction modality, lack of human intelligence, availability issues
Hybrid intelligence	(Mostly) intelligence-intensive tasks	Human–machine interaction, synchronization	Scalability, machine-dependent performance

Table I. Summarization of computing paradigms

Mobile data mining (Stahl *et al.*, 2010) as well as location-based computing (Karimi, 2004), further, have leveraged such smart entities as the most eligible candidates to take part in computational processes of all kind (Vij and Aggarwal, 2018; Zhao *et al.*, 2019).

On the other hand, distributed, ubiquitous and cloud computing paradigms, high-speed network connection and communication as well as similar technological facilities have provided a fertile land of opportunities to tame the groundbreaking possibilities. Therefore, not as a completely mold-breaking concept but as a complementary and evolutionary one, Collective Hybrid Intelligence (CHI) has everything to be realized.

Defined as a framework for "*integration and convergence of (intelligent and non-intelligent) capabilities of humans and machines in an organized and structured way to perform a (series of) specific (intelligence- and resource-intensive) computing tasks*," CHI can be considered as a comprehensive, multipurpose and scalable concept.

The notion of collective hybrid intelligence, in addition to intelligence-intensive processes, can also be extended to any human–machine cooperative tasks. Basically, besides sharing the intelligence, the agents can collaborate for, e.g. data collection, testing, validation, ideation and any process that needs a remarkable amount of cooperative efforts.

The CHI, principally, is an umbrella term to describe various ways of leveraging human–machine cooperation and collaboration to come up with solutions for highly complicated and sophisticated problems. In other words, this study is aimed to put forward a brand new vision for enabling humans and machines (in a bilateral way) to establish some type of super-collaboration.

According to the concept, every single entity with sufficient capabilities and qualifications can be a nominee (i.e. potential contributor) to participate in a computational process. In this regard, in the presence of appropriate utilization mechanisms, e.g. computing platforms and portals, various computational and processing tasks of interest can be performed in (almost) everywhere and at every time (Figure 4).

Owing to wide range of possible situations, requirements and computational problems, the proposed framework is presented at the conceptual level. Doing so, in addition to make it flexible so as to be able to fit various needs, implementation of different instances in different contexts will be facilitated. Therefore, the architectural notes in the following sections present a high-level view of the framework and its fundamentals (i.e. general organization of CHI) not a specific implementation of that.

Besides proposing a modern computing perspective, CHI is greatly related to the concepts discussed in the previous section. Such relationships are illustrated in Figure 5.

4.1 Architectural notes

From a general point of view, the conceptual architecture of a typical realization of CHI-based systems can be depicted as in Figure 6. According to this conceptual representation, any practical realization needs a complicated and multi-level implementation. Specifically, some mechanisms are required for distributed task management, result aggregation, integration and validation. The general workflow of such a system can be described as follows.

After specifying the goal [i.e. problem(s) to be solved] and decomposing it into subtasks, the active agents will be identified/selected based on some criteria. Then, the task management component firstly analyzes the (ordered) task to determine its requirements, including primary resources, priority, estimated completion time, etc. Then, the appropriate available resources will be specified for performing the task in an efficient way. Decomposition of the initial task into several subtasks for distributing them over the computing network is the next step. Such a partitioning was based on the type of tasks and

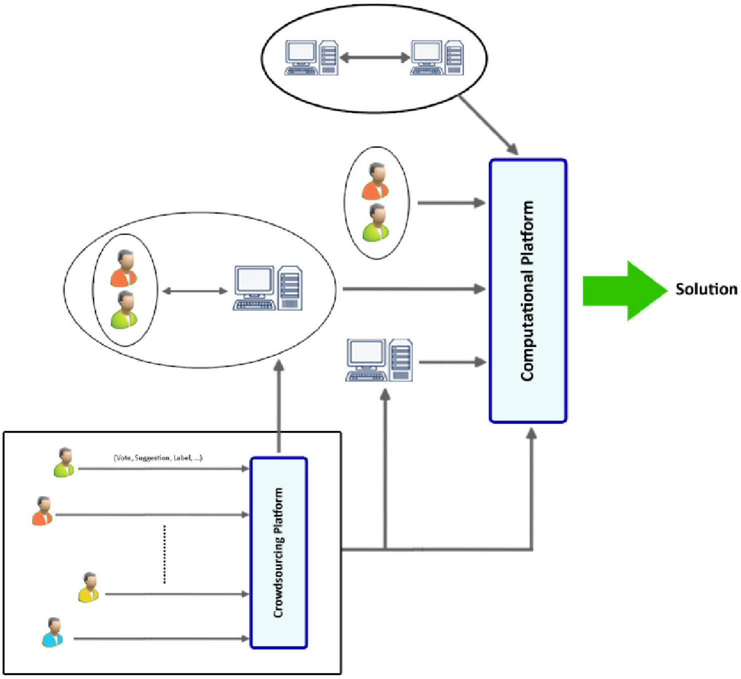

Figure 4. Simplified schematic of CHI workflow

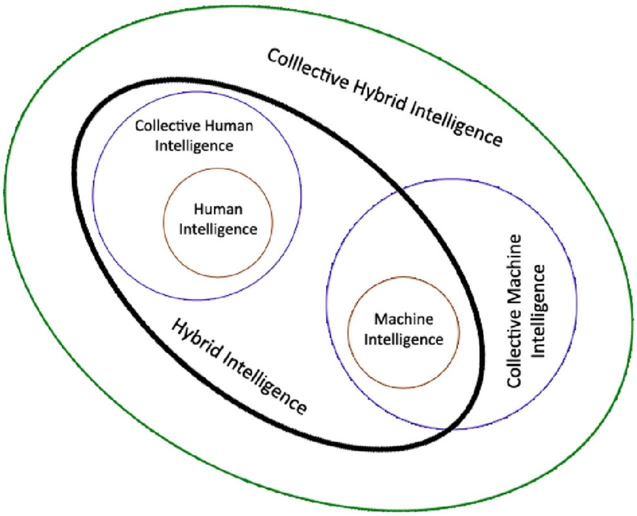

Figure 5. Relationships between CHI and related concepts

available resources. For example, managing a data-intensive task is far different from a time-dependent one. Finally, the subtasks will be assigned to the selected agents. Moreover, the task management component is in charge of aggregating and integrating the results, i.e. agent-generated responses. The agent management component maintains a complete and

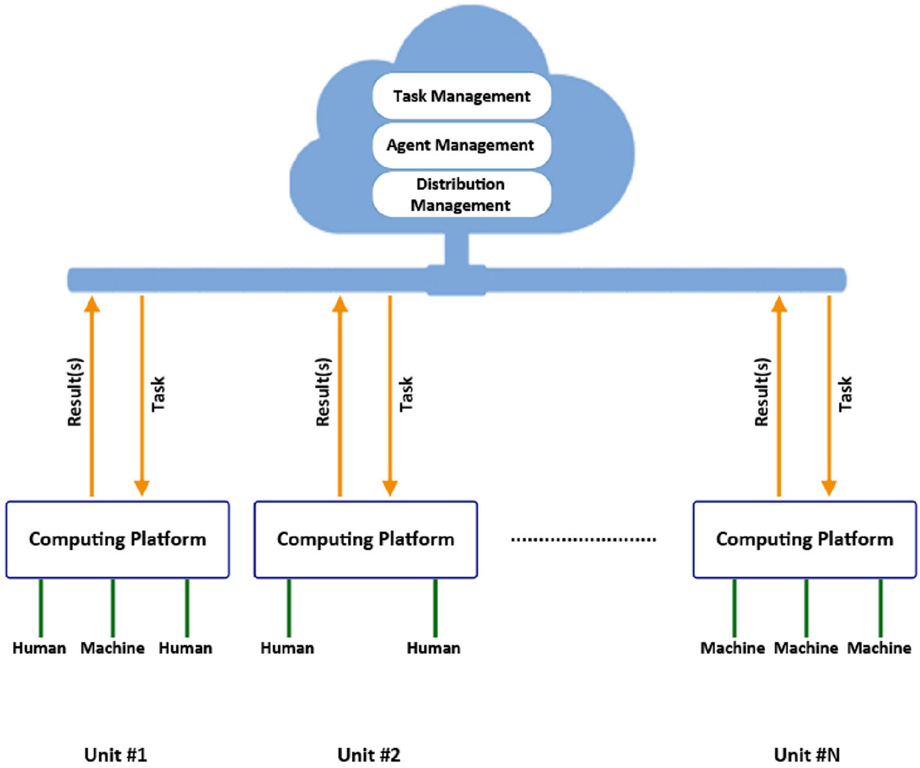

Figure 6. Conceptual architecture of a CHI-based system

continuously updating profile (list) for all the available agents and their processing and computational capabilities.

The agents will be prioritized based on some major factors, such as availability, active resources and (quality of) performance history. Those information plays a vital role in assigning tasks to the agents. Generally, two main scenarios can be considered for the task assignment process.

First, the tasks will be presented in a task pool, then the volunteer agents in an auction-like process and based on their capabilities, resources and also problem requirements will take responsibility of performing those tasks.

In the second approach, those agents in the ready queue that match the requirements (such as being in an appropriate geographical location, having a specific resource, etc.) specified by the task coordinator; will be selected to perform the tasks. Then, the tasks will be performed by the participants and the outputs will be returned to the cloud-based server.

Finally, the gathered results will be integrated and validated so that they become usable for the intended goal(s) (Figure 7).

To demonstrate how such an approach may be benefited, three example scenarios are described in the section 6.

According to the aforementioned workflow, as a high-level viewpoint, such a system should be shaped over a cloud-based infrastructure to support huge communication and computing processes. To manage the computing procedures, including task management and integration, a distributed computing platform should be leveraged as a middleware.

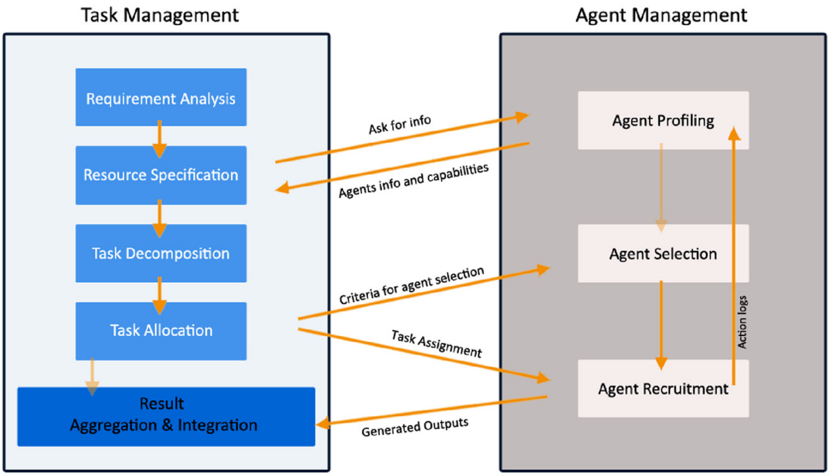

Figure 7. General internal workflow of CHI

However, handling such possibly huge computing processes may face with many difficulties; thanks to the emerging fog (Bonomi *et al.*, 2012) and edge computing (Shi *et al.*, 2016) concepts, they can be managed efficiently.

As illustrated in the layered architecture (Figure 8), on the top of the stack, a web service is in charge of providing participant agents with appropriate interface – similar to existing crowdsourcing platforms- so that they could perform assigned tasks.

One important aspect of adhering to the CHI principles is leveraging maximum benefits of distributed computing. Specifically, thanks to flourishing of mobile crowdsourcing and data mining; location-based intelligence and computing are pervasively available. Moreover, thanks to ubiquitous smart devices spread globally, including smartphones, gadgets, laptops, closed-circuit cameras, PCs and state-of-the-art game consoles, we are witnessing a highly distributed, untamed computing potentialities.

To capture such diverse dynamics, there are needs to well-organized and purposeful mechanisms and platforms. As the inspirational practical examples of how humans' power

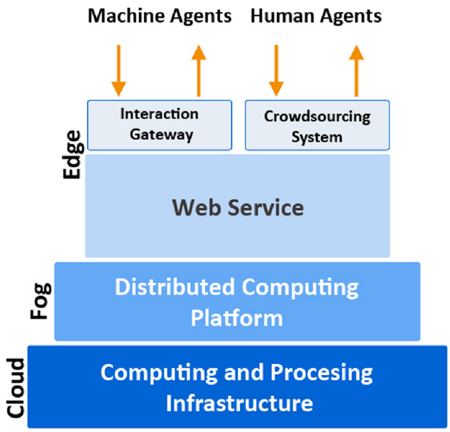

Figure 8. Layered architectural representation of CHI

could be used and converged, general- and specific-purpose crowdsourcing platforms, such as (Willis *et al.*, 2017; Peer *et al.*, 2017), are worth studying. In addition to take advantages of current crowdsourcing systems, there may be need to design customized systems to fit the case-specific requirements of computational processes.

From another point of view, establishing reliable mechanisms to organize machines' participation and joint work is an essential requirement. In this regard, development of platforms through which machines could interact and collaborate with each other put forward priceless benefits. Previous efforts of this kind such as Robot-specific social networks (Wang *et al.*, 2012) and social internet of things (SIoT) (Atzori *et al.*, 2012) are great sources of inspiration, by the way.

4.2 Realization models

Based upon the proposed framework, machines, as passive entities, are thought to be in charge of providing computational power and processing infrastructure. Therefore, a PC, laptop, supercomputer and even a smartphone or a large network of computers can be regarded as an independent/hybrid agent in the process. From another viewpoint, the human agent besides his traditional roles (user or supervisor) can present a cooperative and interactive character to assist machines in a broad range from collecting training data sets to perform more complicated tasks, such as result validation and verification. Moreover, decision-making on how to distribute tasks between humans and machines is another important and determining consideration. Such a decision affects the bilateral human–machine cooperation as well as resource management. For example, inefficient separation of an intelligence-intensive task between agents may result in wasting times of machines for what those are not very powerful in and imposing complex and heavy computations (that take too long to complete) on humans. To avoid such flaws in realization of the CHI, two general task separation models are presented.

The first one is a homogeneous model in which the tasks will be presented to the machines and humans in a distinctive manner. Then the results produced by each group will be collected and integrated. In the final stage, both results generated by the machine and human will be combined to produce the expected output (Figure 9).

As a heterogeneous solution, the second model is based on using direct human–machine collaboration in the form of hybrid intelligence from the very early steps (Figure 10).

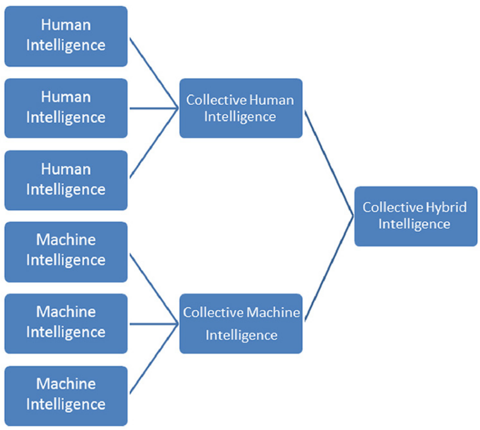

Figure 9.
Homogeneous realization of CHI

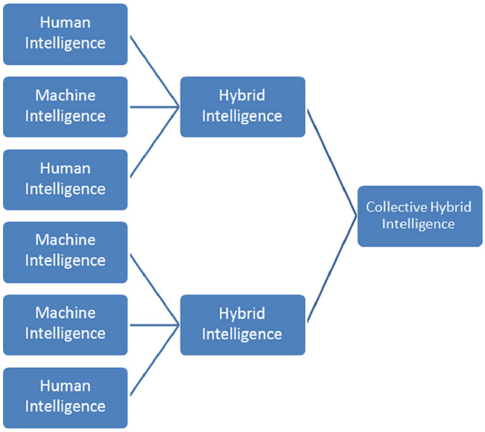

Figure 10. Heterogeneous realization of CHI

As mentioned earlier, such a separation of tasks and duties comes in handy for managing available resources, costs, completion time and accuracy as well as striking a balance between efficiency and complexity. This is mainly because, not all tasks are appropriate for all agents and not all problems can be solved in an identical way.

The first model, in essence, is the appropriate choice for the mostly resources-intensive tasks or those ones in which requirements and different aspects of tasks are clearly distinctive and separable. In such a situation, this kind of organization can drastically resolve unnecessary complexities. Accordingly, intrinsically hybrid and complicated processes are better to be organized based on the second realization model.

4.3 Discussion

Generally, crowdsourcing-based and distributed processes introduce some intrinsic challenges and difficulties. Consequently, when it comes to synthesize these processes in an organized and cooperative workflow, facing unexampled and incidental challenges are inevitable. As a matter of fact, in spite of its presumed efficiency and applicability, the major challenge CHI struggles with is a cost-effective and reliable implementation. However, the authors are working to come up with such a solution, it seems there are needs more efforts and time to that point. In this respect, to cope with such issues, some essential considerations [including general (1-4), human-centric (5-7) and machine-centric (7, 8) ones] should be taken into account as follows.

4.3.1 Problem formulation. CHI is basically a high-level solution when the problem is a multidimensional, computationally expensive and usually large-scale one. Such a problem, on its own, addresses several intrinsic complexities that may affect the effectiveness of the process. Therefore, there is need to a preliminary analysis step for specifying different aspects of the problem, the category it belongs to, required resources and so on. Such a pre-evaluation provides necessary information to map the problem to the appropriate realization approach. As the matter of fact, the heart of a system constructed based on the proposed concept is efficient separation of duties (tasks) among the participants and this largely depends on the problem formulation process.

4.3.2 Distribution management. The distribution of tasks among agents and managing them is one of the most important and critical issues. Owing to intrinsic heterogeneity of the participant agents in the process, managing and coordinating them so as to result in providing most efficient and possible performance is of the highest importance. Analyzing performance log records, real-time agent management facilities as well as continuous monitoring and efficiency assessment are among the major considerations in this regard.

4.3.3 Interaction facilitation. The communication among various agents involved in the process and their interaction with control/management unit are other essential issues that should be taken into account. In addition to demand for (possibly) some new communication protocols, there is an essential need to an interface (agent interaction modality), e.g. a task management system such as Amazon Mechanical Turk, through which agents can interact with the system, perform the assigned tasks and submit the results.

4.3.4 Availability management. Although the availability issue is a well-studied topic for distributed systems (Kondo *et al.*, 2008; Rawat *et al.*, 2016); dealing with similar problems in the context of the proposed concept is way different and more challenging. Specifically, there should be several strategies for the cases in which human participants refuse to complete tasks in the scheduled time. Such problems are particularly associated with voluntary participation. The case will be more critical if the unavailability occurs in hybrid (heterogeneous) processes by each of the participant parties.

4.3.5 Participation engagement. In the context of crowdsourcing, attracting participation is an influential and challenging issues. Because relying on volunteer participants could not guarantee the desired performance in most of cases (Mao *et al.*, 2013; Baruch *et al.*, 2016); some strict, foolproof and reliable engagement strategies are needed. According to the best practices (Pilz and Gewald, 2013; Khoi *et al.*, 2018), monetary incentives can be convincing for most of humans. So, when it comes to recruiting professional (expert) crowdworkers, higher costs (and even other incentives) may be imposed. Further, using non-human agents (i.e. machines) is even more difficult and troublesome. A probably working suggestion is establishing a cloud-based market in the reverse direction through which individuals could sell their own machines' capabilities by enrolling in available computational processes. Then, they will be paid per completed tasks.

4.3.6 Quality assurance. One of the most important concerns in human-mediated processes in general and crowdsourcing in particular is the quality (i.e. accuracy and preciseness) of performance (e.g. submitted results). Despite efforts have been made to cope with this issue (Daniel *et al.*, 2018), its unfavorable consequences can be severe in complicated and multidimensional projects. As an example, low quality labels in a crowdsourced image annotation process address very limited negative effects in contrast with inaccurate evaluation of a machine learning model. In addition to considering strict criteria for crowdworker recruitment, monitoring participants' performance and adhering to rigorous task assignment standards are some practical steps to ensure the quality of the completed tasks.

4.3.7 Adversarial intentions. Untruthful workers and those with adversarial intentions in mind (Difallah *et al.*, 2012; Steinhardt *et al.*, 2016) can threaten any crowdsourcing process. Hence, trust management (Yu *et al.*, 2012; Feng *et al.*, 2017) plays a key role in participant recruitment and task assignment processes to deal with inaccurate and wrong submissions or even organized attacks aimed at affecting the process. Because there are situations in which some private information can be revealed (Boutsis and Kalogeraki, 2016), relying on untrusted workers may result in privacy breach and violation. Therefore, the needs for identifying malicious participants (both humans and machines), neutralizing wrongdoings and preserving privacy (for information and even participants (Kajino *et al.*, 2014) are a must.

4.3.8 Machine inefficiency. Owing to differences in hosting systems' configuration, implementation, initial training data and so on, the efficiency of (even same) machine learning algorithms may vary case by case. For this reason, various machines introduce various levels of efficiency for different problems. In this regard, there should be some mechanisms to manage such unbalanced capabilities and performance – specifically in the case of hybrid collaboration- to make the computational process as reliable as possible.

5. Example scenarios

Explaining the operation of a system that works based on the proposed concept, three motivating example scenarios are presented in this section. Applications of CHI are not limited to these cases; however, they could be regarded as inspirational instances to generalize the underlying concepts.

5.1 Collective hybrid intelligence for computing tasks

In this example, the given goal is to recognize similar images from a large data set and annotating them to obtain appropriate results. To participate in this location-independent (and mostly intelligence-intensive) task, there are no specific criteria for human agents but their position in the task allocation queue. On the other side, being equipped with Open CV machine vision library is the specified criterion for the machines. Then, such machines will be selected from the ready queue to be a participant. Though, there are various methods for assigning tasks to the workers (agents), "In the context of this example, the tasks are divided into two groups: Resource-intensive and cognitive ones. Thanks to the development in the field of machine vision and image processing, finding similar images, in general, is not a difficult task. Therefore, these relatively time-consuming tasks that do not need high level of cognitive ability will be assigned to the machines. Moreover, machines are in charge of performing initial automatic annotation. To guarantee the accuracy and efficiency of annotations, for a specific image or a set of images that convergence rate, similarity of classification and annotation are less than a determined threshold, the results will be assigned to humans for further considerations. Moreover, the output of humans' efforts, after analysis, may be leveraged as a gold standard to evaluate machines' performance. Also, such human-generated data can be used to train machines.

5.2 Collective hybrid intelligence for autonomous urban vehicles control

One of the most important issues in controlling autonomous vehicle is need for an accurate, up-to-date and comprehensive map or some advanced peripherals to provide environmental information in real-time, (Vochin *et al.*, 2018; Bayat *et al.*, 2018) and references therein. In this example, the application of CHI in providing such a specialized map is considered. Doing so, in one side, human agents should collect information from different streets of the city including rush hour situations, the safest paths, detours in various times and conditions. Moreover, their own experiences and recommendations for navigation in such situations are of the high importance. On the other side, traffic cameras and other urban monitoring sensors provide specialized machines (i.e. specific-purpose computers) with some real-world information on different situations of the city. Alongside with satellite and global maps information, such machines which leverage advanced algorithms can come up with some navigation patterns for the autonomous vehicles. Finally, fusing these two types of intelligence – that could be gathered asynchronously – can be used for predictive control of such vehicles within different streets of a crowded city in different times.

5.3 Collective hybrid intelligence for human–robot cooperative surgery

Human-robot cooperative surgery is another context that adhering to collective hybrid intelligence principles may improve its workflow and performance. As an imaginary scenario, the CHI can facilitate a complex operation as follows: depending on the case, the previous experiences and information are gathered from experts. Such invaluable data will feed the automatic robotic arm(s) with the necessary information. In the case of any unprecedented issues or exceptions, if the (expert) system could not find any reliable solution (recommendation), the experts who are monitoring the operation will present their ideas (suggestions) based on the situation and machine's feedback. Then, the integrated responses will be sent to the robot as the collective advice. Needless to say that, in this case, all the mentioned processes should be performed in real-time.

6. Conclusion

In this paper the notion and general concept of CHI as a new complementary computing and automation concept is proposed. The main idea behind the Collective Hybrid intelligence is leveraging humans and machines' capabilities in a new manner to maximize the efficiency of human–machine cooperation and collaboration. The major building blocks of the presented framework are some well-experienced and successful approaches, namely distributed computing, collective human intelligence, human computing, hybrid intelligence and collective machine intelligence. To support the introduced idea, its different realization models, the conceptual architecture and workflow are delineated and discussed. The authors anticipate that this concept can provide unprecedented functionality and performance for human–machine-cooperated processing and computing procedures in the near future. Meanwhile, it is emphasized that the proposed idea in this paper is in its early stages and there are still several unanswered questions and challenges yet to be resolved. Specifically, the implementation of a real-world system based on the presented framework is future work of the authors.

Notes

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