3D SpaceQuantumIndexation and Computation via VoxelNET to Enhance 3D Cognitive Systemisation

-Reasoning, Raycasting and GeoLoacted Voxels

Charlotte Sennersten
Mineral Resources
CSIRO
Australia
email: charlotte.sennersten@csiro.au

Craig Lindley
Data 61
CSIRO
Australia
email: craig.lindley@csiro.au

Abstract—**A global recursive equal-volume spatial quantization and indexation system can unify access to, use and perform volumetric computations across diverse fields to provide a volumetric evolution from the current 2D internet. A unifying spatial framework has been developed to demonstrate this alternative. The framework supports cognitive spatial analytics incorporating different datasets, advanced AI systems, human decision support, robotic and autonomous systems, and many other applications for which three-dimensional spatial structure is important. Domains in question can include a variety of sensor inputs, including environmental, physiological, neural, material, chemical, optical, locational (e.g. GPS and lidar), etc.. Sensor data in diverse domains is used to create domain-specific models for analytics and decision support, and for models of human cognitive performance amenable to automated, machine implementations. The system includes a unified, hierarchical spatial quantization system with time series data and fixed, locational, and mobile volumetric structures. The framework supports data, information and knowledge management and can also be used to manage the distribution of computational loads. It can also support new computing paradigms, e.g. tracking the spatial locations of geographically dispersed computations linked by quantum entanglement.**

Keywords-Spatial Cognition; Voxelisation; Computation; Sensor Integration.

I. Introduction

The main objective of this paper is to collate many years of work unifying and systemizing qualitative and quantitative data using a 3D spatial framework called the VoxelNET platform. The platform provides a ‘digital twinned’ world, a digitized replica of the volumetric physical world, a unified, hierarchical spatial quantization framework for location and movement tracking and volumetric computations across diverse fields. The main fields demonstrated over the years have been gaming, mining, space and robotics -where decisions mainly have been about volumetric comprehension, timing, and economy.

The goal of the computer and cognitive science research is to provide the software engineering implementation with requirements for a systemized volumetric infrastructure so people/users can share and understand otherwise siloed volumetric data.

An analogy might help to explain why all this is important. Imagine yourself scuba diving and navigating through water. You may not know what is ‘up’, ‘down’, ‘left’ or ‘right’ and available sensors do not capture the environmental, physiological or optical data in its 3D context. VoxelNET and its indexation helps to geo-index, cross-correlate, compute and contextualize the data in its global volumetric architecture. Our research purpose is to make sense of sensed and captured data in this 3D context.

The platform sits exemplifies Internet 4.0, Mining 4.0, Space 4.0, Industry 4.0 and other *X* 4.0 concepts representing the full integration of sensors, information and operations systems within the 3D and 4D structure of the world. This includes elements such as: cyber-physical systems (CPS), the internet of things (IoT), industrial internet of things (IIOT), cloud computing, cognitive computing, and artificial intelligence (AI). X 4.0 systems are characterized by the interpenetration of the physical world using data, computation, analytics and control systems. The result is an evolving large-scale infrastructure that includes the data interconnectivity required for integration, together with many diverse systems and components for modelling and analyzing the world. The total infrastructure hierarchy for control happens by a synthesis of human, automated and autonomous decision making at different levels. Decision making within such an integrated system is both heterogeneous and highly distributed. Raising the overall intelligence of X 4.0 systems requires higher levels of coordination. A critical element of this is the coordination of mapping and decision making regarding three-dimensional (3D) space. However, current internet concepts and technologies are neither inherently spatial nor three dimensional. Since X 4.0 is heavily concerned with data and computational integration of the physical world and its contents, which *are* inherently 3D and spatial, the deployment of a universal 3D spatial infrastructure can be a critical element in accelerating the evolution of these systems. A universal 3D spatial infrastructure can provide the 3D *spatial context* of X 4.0 data, models and computations, facilitating higher level cognitive functions that can process not only *what* is happening *when* (the

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current dominant paradigm for X 4.0), but also *where* it is happening. This amounts to the incorporation of spatial awareness and spatial cognition into X 4.0 systems for indexation, computation, analytics and display.

Previous work [1], [2]) has described the VoxelNET research prototype system, a 3D spatial indexation system and a computational infrastructure used to support volumetric representations and decisions. VoxelNET is a demonstrator for a broader concept of a universal 3D spatial data framework that can potentially provide the kind of spatial framework required for X 4.0.

VoxelNET quantizes the Earth into default 1 m^3 voxels that penetrate Air, Space, Water, Rock, and Soil so these natural continuous material distributions can be included in the Internet of Things (IoT), which otherwise tends to focus on separate artefacts or objects that are artificially produced [1] [2]. This allows the combination of representations of what is artificially made with what occurs naturally together with their respective locations, orientations and spatial distributions over time.

This can be extended beyond the Earth to include the Moon, Mars and other solar system objects. Of course, these objects have their own coordinate systems. This is catered for by the underlying mathematical formulations of coordinate systems, which can include alternate geometries (e.g. ellipsoidal, spherical, Cartesian) modelled as local coordinate systems within specified larger scale spatial coordinate reference frames within which they are situated and mapped by spatial transforms. The required transforms must specify a particular location (typically in 3 dimensions) and orientation (e.g., in terms of rotations around 3 axes) at a specific time (or epoch), together with a specification of velocity at a particular epoch. These parameters can be used by active functions to compute locations at different times.

The VoxelNET capacity for representing multiple coordinate systems can be used to locate objects and material masses within locational coordinate reference systems, as well as larger scale global reference frames within which local frames can be situated. Spatial reference frames are static, persisting over time, and voxels within the 3D structure are referred to as *location voxels*. The VoxelNET database allows data to be volumetrically indexed and associated with unlimited amounts of data for specific volumes. The volumetric indexation of locations is static. Objects and materials are represented using the concept of *material voxels.* These are volumetric representations of material masses and objects moving through static geolocated voxels. Representations of material voxels can be rescaled, combining multiple material voxels into larger scale voxels, or subdividing them into smaller scale and potentially mixed and/or materially/chemically transformed voxels, and aggregated or disaggregated into malleable shapes. This capacity has been used, for example, to map the removal of materials from a mineral resource block in the ground, through sequences of mixing and separating transforms via processes such as blasting, excavation, loading onto haulage, unloading, stockpiling, etc., to create provenance records for material entering a mineral processing plant.

This paper elaborates on a number of topics associated with this integrating vision of the VoxelNET system, including: general issues around spatial cognition, the integration and use of environmental and physiological sensors, management of distributed computation, understanding and integrating human cognition in a broader spatial context, and potential application in quantum computing. Section II. describes spatial cognition and associated concepts, while subsequent sections describe III. Sensors for Environment and Physiology, IV. Discretized Computation, V. VoxelNET, Brain, Gaze and Ray Casting - how to bind it together, and VI. Parallel Processing and Quantum Computing.

II. Spacial Cognition, Syntax, Awareness and Cognition

Spatial cognition involves not one but many specific abilities. These include locating points in space, determining the orientation of lines and objects, assessing location in depth, apprehending geometric relations between objects, and processing motion, including motion in depth. Building upon these details, spatial cognition includes awareness of locations and orientations in space, spatial relationships between and among objects and materials, how to navigate through an environment, and how to manipulate objects and materials by hand or machine for a large range of purposes. Zimring and Dalton [3] describe 'Linking objective measures of space to cognition' mainly focused on how people acquire, store, and represent information about directions, distances, and locations in the large-scale physical world. The authors also refer to Space Syntax in terms of "…rigorous measurement of the layout of physical settings and observation of people moving through it; environment and behavior studies have examined self-report behavior such as think-aloud protocols and sketch maps as well as movement in real-world settings; cognitive science has explored and modeled cognitive processes." [3].

Most researchers have found that cognitive representations, or their presumed externalizations such as sketch maps, are often distorted. Often people learn topology first and then develop more coordinated metric relationships later. For example, one might know that a shopping center is beyond the school but not know how far. People seem to have greater difficulty representing complex settings. In the realm of IoT and digitization, spatial navigation needs to be extended to digital 3D world representations, discretization, digital operations and digital 2D and 3D browsing in order to understand, design and optimize the operation of systems within their spatial context.

Moreover, as Thrift [4] puts it, "The fabric of space is open-ended rather than enclosing." and "we are increasingly a part of a 'movement-space' which is relative rather than absolute but which … relies on an absolute space for its existence".

Spatial awareness is defined as "the ability to be aware of oneself in space. It is an organized knowledge of objects in relation to oneself in that given space and the relationship of these objects when there is a change of position." [5]. Spatial awareness is essentially a question of making a trade-off between local visual information (which can be seen from a single standpoint) and global spatial information, which includes visual data of the rest of the environment, but also haptics and symbolic representations of space such as maps. To be efficient, a person navigating must maximize their acquisition of global information while minimizing local information, achieved by recognizing when they already comprehend enough about their immediate surroundings and hence intuitively seek the next key location that permits a sudden increase in novel environmental data.

As thinking individuals, we are cognitively calculating ourselves through the physical and digital world i.e., the logic of the system. “The upper bound of human brainpower has been calculated to be 2 x 10^{16} calculations per second. If computational power continues to conform to Moore’s Law, then by 2030 just an ordinary PC should compute at around 10^{16} instructions per second [6]. There is also an increasing ubiquity of hardware and software, which means that computing can take place in many locations” [4]. Moreover, islands of computational power analogous to individual human cognitive processing capacity are increasingly being integrated in seas of interconnectivity. This raises the need for collective cognitive frameworks for the unification of individual nodes of cognitive capability into larger scales of cognitive capability interconnected by much higher bandwidths than native human communication mechanisms (i.e., speech, non-verbal communication, technologies such as writing and drawing).

While navigating on and through Earth we can map physical reality using sensor data. Extending this to X 4.0 systems of systems, we need to be able to situate and index the information so we can translate context and invite people and machines to interact in a ‘ground-truthed’ collective digitized environment. A location method such as GPS is an estimate of a location, while the "ground truth" is the actual location on earth [7]. Ground truth refers to information collected on location, as opposed to information inferred from remotely sensed data. Ground truth allows image data, for example, to be related to real features and materials on the ground. The collection of ground truth data enables calibration of remote-sensing data, and aids in the interpretation and analysis of what is being sensed. Ground truth is a best representation of the geolocated information and its three dimensions of 360-degree landscape so we can share, interact and specify where we and things are, wayfinding ourselves by using various individual coordinate systems.

III. COGNITION [PHYSIOLOGICAL SENSORS] AND SPACE [ENVIRONEMNTAL SENSORS]

How do we understand cognitive choices and how can we assist and design for our affordances versus shortcomings?

A. Attention, Heart Rate, Arousal and Reasoning

Human and animal intelligence is facilitated by several forms of memory, including a long-term semantic memory (SM) of abstract concepts and types, a short-term memory (STM) and a long-term episodic memory (LTM) of experiences. Humans also reason about their environment and use a so- called Memory SketchPad or working memory (WM) for active thinking processes that combines both new and old information to solve problems, such as finding a path, creating and negotiating a trajectory in the case of spatial reasoning [8].

Our eyes are the main physiological instrument that provides data for use by the cognitive system to navigate through a 3D space or a maze, and visual attention directs the eyes to features of interest in the visual field that are unconsciously selected for relevance to a problem-solving situation [9]. WM is used by cognitive processes to synthesize this kind of data into problem solutions.

Heart rate, heart rate variability, and other indicators of physiological arousal such as skin conductance are other unconscious responses to stimuli such as environmental and social factors.

All these physiological responses can be measured by physiological sensors such as infrared diode corneal reflection for eye gaze tracking to study visual attention, heart rate and its variability using pulse monitoring, and skin conductance measurements to study arousal [10] [11]. fMRI can be used to understand the spatial distribution of brain activity via increased blood flow.

Eye gaze tracking can be used to gain insight into the control of visual attention to gain data used by cognitive processes for problem solving, while unconscious physiological data can be used to infer emotional states relevant to cognitive goals and biases, e.g., as input to affective computing systems. The spatial context of these processes is crucial for understanding their details and a general external spatial reference frame can be used to locate measurements and external phenomena in relation to which cognitive processes are being performed.

B. Lidar Pointclouds, Images and Objects

Numerous environmental sensors measure different states of our environment and optical sensors such as lidar can map spatial details of local physical environments in detail and store the information to computer memory. A Lidar scan usually has a geolocated origin point such as a GPS point so the location of the Lidar scan can be situated in the world. Lidar gives the structure of a space, it’s lay-out in 3D. RGBD and Photogrammetry combine image and depth. An image in a traditional sense is a 2D representation of the world providing inputs to image processing that can distinguish features via pixel color and contrast features to distinguish depth parameters [12]. A universal 3D spatial reference frame can be used to store all of these kinds of data for use both in real time and for retrospective analytical studies across agents and situations.

IV. COMPUTATION

Our brains and computers perform computation. Computation by definition means: I. the action of mathematical calculation, "methods of computation" and II. the use of computers, especially as a subject of research or study. In theoretical computer science and mathematics, the theory of computation is the branch that deals with how efficiently problems can be solved on a model of computation, using an algorithm. Humans, animals and robots use algorithms to perform tasks.

VoxelNET discretizes volumetric data in a systematic way and this can be used as a computational framework so we use computer/computing science as a baseline in parallel with cognition i.e., reasoning when looking into how to progress the design of the system for both machine and human benefit and comprehension.

Thrift writes “In a world in which numerical calculations are being done and redone continuously, static representation becomes subordinated to flow (not least because ‘the image, in a traditional sense, no longer exists’ [13], the nomadologic of movement becomes the natural order of thought. The world is reconfigured as a global trading zone in which network forms, which strive for coordination, are replaced by flow forms which strive for observation and projection.”. He continues “Most importantly, I shall argue that the sheer amount of calculation that is now becoming possible at all points of so many spaces is producing a new calculative sense, which I will call ‘qualculation’ [14].” Thrift [4] includes factors like speed, faith in numbers and limited numerical facility available in the bodies of the population also involving a different sense of number and counting and series. It is important that the use of numbers varies with context and is not a discrete activity carried out for itself.

The computation field is divided into three major branches: automata theory and languages, computability theory, and computational complexity theory, which are linked by the question: *"What are the fundamental capabilities and limitations of computers?"*. To this we can add, what are the fundamental capabilities and limitations of the human brain and reasoning capability for computing and interpreting a holistic digital eco system?

A. Computational Complexity Theory

Computational complexity theory considers not only whether a problem can be solved at all on a computer, but also how efficiently the problem can be solved [15]. Two major aspects are considered: time complexity and space complexity, which are, respectively, how many steps it takes to perform a computation, and how much memory is required to perform that computation [16].

In order to analyze how much time and space a given algorithm requires, computer scientists express the time or space required to solve the problem as a function of the size of the input problem. For example, finding a particular number in a long list of numbers becomes harder as the list of numbers grows larger. If we say there are n numbers in the list, then if the list is not sorted or indexed in any way we may have to look at every number in order to find the number we're seeking, which will result in an average search time of n/2. We thus say that in order to solve this problem, the computer needs to perform a number of steps that grows linearly with the size of the problem.

B. Discretisation

In applied mathematics, discretization is the process of transferring continuous functions, models, variables, and equations into discrete counterparts. This process is usually carried out as a first step toward making them suitable for numerical evaluation and implementation on digital computers [17].

C. Quantisation

Quantization is the concept that a physical quantity can have only certain discrete values. Electrical charge, energy, light, angular momentum, and matter are all quantized on the quantum level. Also, the energy levels of electrons in atoms are quantized. In a computational system, quantization is typically the same as discretization, where the size of quanta involves a tradeoff between storage space and processing time on one hand, and the accuracy of physical simulation on the other; large quanta are easier to store and process, but less accurate for the simulation or representation of continuous physical phenomena. Quantization does not need to be linear, but can be a nonlinear map that partitions a numerical space and represents all of the values in each subspace by a single value [18].

Quantization errors are errors arising from the loss of information created by the mapping of continuous phenomena into discrete artificial quanta. The scalability of VoxelNET location and material voxels facilitates the optimization of voxel size in relation to the spatial frequency distributions of data, as well as the management of tradeoffs between quantization errors and computational space/time complexity.

D. Size of Files

To progress in a 3D world with sensors mapping real world environments we need to subdivide information in a discrete and quantized manner; this is a fundamental principle of digital computers, for which all continuous values must be represented in binary numbers. In many cases there are clear criteria for quantization scales. For example, to represent a varying phenomenon, basic sampling theory shows that samples of the phenomenon should be taken at a rate (i.e. the inverse of temporal or spatial quantum size) of at least twice the frequency, or half the wavelength, of the highest required frequency component of the sampled phenomenon. A lower rate than this will lose information, while a higher rate will add no new required information. For cognitive attention, the quantization scale is related to the importance of a sensory feature for the cognitive task at hand and its neural or computational transformation into a level of abstraction suitable to problem solving. E.g., in digital modelling of a Field of View (FoV), see Figure 1, we may need to represent digitized content supporting a task at high resolution, leading to large data sizes, while the background and middle ground of the FoV may be of less importance and therefore appropriately represented at a lower resolution.

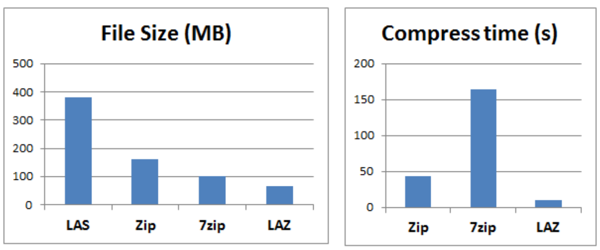

Figure 1. Typical lidar file sizes around 300-400MB.

Digitized content includes optical sensor information and computation for analytics and display.

V. VOXELNET, BRAIN, GAZE AND RAY CASTING

How do we bind together the external world with computation and human cognition in a coherent systemized way.

The technical solution to this described here is the VoxelNET system. By default, VoxelNET indexes and quantizes the Earth in equal volumetric computational units, see Figures 2, 3 and 4.

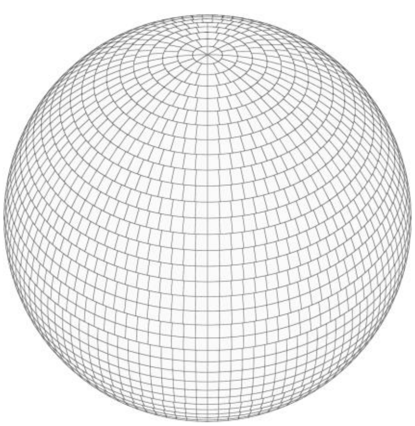

Figure 2. VoxelNET Earth quantization.

On one hand the VoxelNET database represents a linguistic interpretation and representation of the physical world while the client needs to replicate and represent the world in a direct 3D FoV manner. The VoxelNET infrastructure spatially parses all 3D objects and data in the world. The voxel indexation makes it possible to directly point towards a direct volume without lengthy descriptive relations in order to reduce time and space complexity. The volumetric context of a volume provides context information that points alone cannot. Equal volume quantization allows analyses to be conducted across numerous voxels which nevertheless have a comparable quantization of the world and therefore consistent and commensurable volumetric interpolation and averaging of data points.

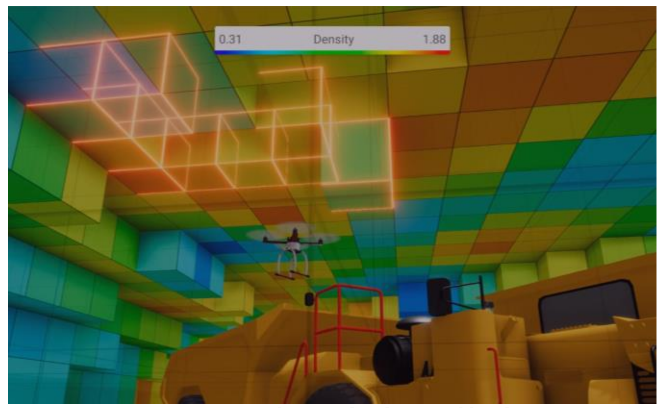

Figure 3. VoxelNET at local regional level.

A. *Gaze into the world -Ray Casting and Ray Tracing*

Ray casting is a rendering technique used in computer graphics and computational geometry making use of the same geometric algorithm as ray tracing. Ray tracing is a rendering technique that aims to simulate the way light bounces off objects, in turn creating more realistic shadows, reflections, and lighting effects. This ensures that the computer isn't wasting processing power on objects the camera doesn't see (compare FoV) while producing more realistic lighting effects. The ray casting method is used in addition to eye tracking, so it is possible to log what a user is looking at in the 3D digital/physical world.

B. *Eyetracking and Eyesteering via Ray Casting to connect with Human Intentions and Actions*

Corneal reflection and infrared light can be used to track the gaze behavior and therefore visual attention of a user interacting with computer content, revealing how things are operated, read, created, etc. to be tracked as an insight into ongoing cognitive processes. Gaze can also be used as an input device into the digital environment here via VoxelNET. The universal volumetric representation system demonstrated by VoxelNET can be used to generalize the use of this interaction and attention analysis technology.

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C. Real World Knowledge Systemisation and Indexation for Human Brains

To connect the external world with the neural physiological foundations of human behaviors and cognition, we need a volumetric representation that can connect or link brain actions with contextual representations of the 3D world that make these meaningful.

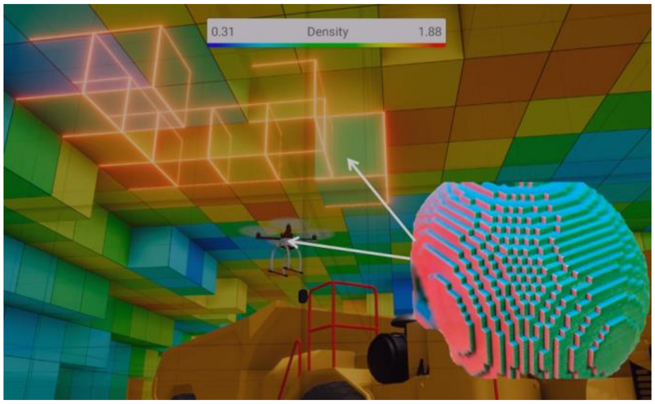

Figure 4. VoxelNET and voxelised brain for world and human knowledge systemization.

In times of neurological programming, machine learning and data mining, it becomes even more important to know and shape knowledge about how we look into the world', what brain regions we activate' and on what basis. Spatio- and spectro-temporal brain data (STBD) are the most commonly collected data for measuring brain response to external stimuli. However, Kasabov says "there is no unifying computational framework to deal with all these types of data in order to better understand this data and the processes that generated it." (2013) [19]. Kasabov's NeuCube model is based on a 3D evolving Spiking Neural Network (SNN) that is an approximate map of structural and functional areas of interest in the brain related to the STBD modeling that integrates various brain data, information and knowledge for a single person into one model.

In the VoxelNET world systemization the brain can be voxelised within a local coordinate system, allowing ray-casting via gaze to bind the two worlds together.

D. Brodmann Brain Areas

When our gaze is distributed across various external stimuli, our brain is processing incoming information in various functional volumes. As Kasabov puts it "The brain is a complex integrated spatio-temporal information processing machine. An animal or a human brain has a range of structural and functional areas that are spatially distributed in a constrained 3D space". The brain processes information, either triggered by external stimuli, or by inner processes, such as visual, auditory, emotional, environmental, social, or all of these stimuli together, complex spatio-temporal pathways are activated, and patterns are formed across the whole brain.

If we want to systemize digitized knowledge i.e., the human or the robot operating in the world and also execute 'compute on demand' with these methods we need to know what happens when, how and where. It is also a matter of how we have people and humans coexisting in the same digital twin world. We want to create a comprehensive digital twin where we create knowledge and not 'black boxes of algorithms/AI' no one understands.

Brodmann areas were originally defined and numbered by the German anatomist Korbinian Brodmann [20], see Figures 5 and 6. Brodmann split the cortex into 52 different volumetric areas and assigned each a number (many of these Brodmann areas have since been subdivided). He published his maps of cortical areas in humans, monkeys, and other species in 1909, along with many other findings and observations regarding the general cell types and laminar organization of the mammalian cortex.

Zilles reports that "A cited reference search in the Web of Science carried out in July 2018 resulted in over 170 000 citations of Brodmann's work, mainly of his monography (Brodmann, 1909). His publications on the cytoarchitectonic parcellation of the entire human cerebral cortex made him a founder of the field of anatomical brain mapping. The number of publications with references to different versions of his maps (Brodmann, 1908a, 1909, 1910, 1912, 1914) dramatically increased since the advent of neuroimaging using PET and MRI, and is still increasing ... The maps have become particularly popular in recent times for localization of activations using functional MRI and for meta-analyses of structural and functional relationships." [21].

The brain locations are of interest when also looking at Quantum Neural Networks (QNNs) as per what neurons are fired where, when and for what reason.

Brodmann's brain areas for humans and other primates are:

- Areas 3, 1 and 2 – Primary somatosensory cortex in the postcentral gyrus
- Area 4 – Primary motor cortex
- Area 5 – Superior parietal lobule

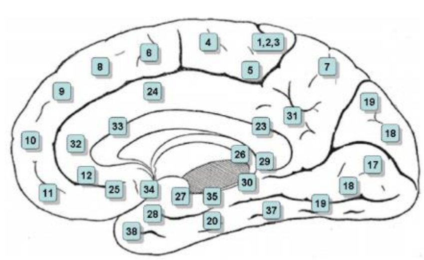

Figure 5. Inner brain 3D mapping [22].

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- Area 6 – Premotor cortex and Supplementary Motor Cortex (Secondary Motor Cortex)
- Area 7 – Visuo-Motor Coordination
- Area 8– Includes Frontal eye fields
- Area 9 – Dorsolateral prefrontal cortex
- Area 10 – Anterior prefrontal cortex (most rostral part of superior and middle frontal gyri)
- Area 11 – Orbitofrontal area (orbital and rectus gyri, plus part of the rostral part of the superior frontal gyrus)
- Area 12 – Orbitofrontal area (used to be part of BA11, refers to the area between the superior frontal gyrus and the inferior rostral sulcus)
- Area 13 and Area 14* – Insular cortex
- Area 15* - Anterior Temporal lobe
- Area 16 – Insular cortex

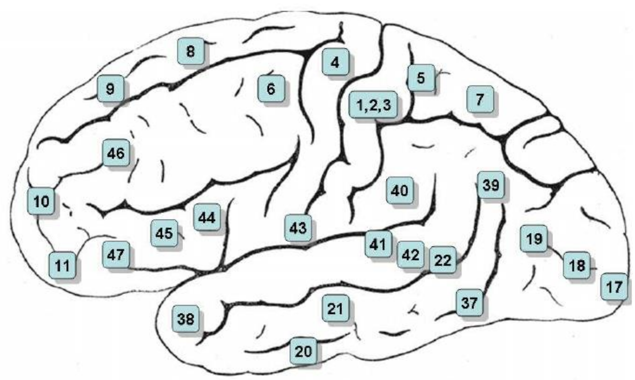

Figure 6. Outer brain volumes [22].

- Area 17 – Primary visual cortex (V1)
- Area 18 – Secondary visual cortex (V2)
- Area 19 – Associative visual cortex (V3, V4, V5)
- Area 20 -Inferior temporal gyrus
- Area 21 – Middle temporal gyrus
- Area 22 – Part of the superior temporal gyrus, included in Wernicke's area
- Area 23 – Ventral posterior cingulate cortex
- Area 24 – Ventral anterior cingulate cortex.
- Area 25 – Subgenual area (part of the Ventromedial prefrontal cortex)
- Area 26 – Ectosplenial portion of the retrosplenial region of the cerebral cortex
- Area 27 – Piriform cortex
- Area 28 – Ventral entorhinal cortex
- Area 29 Retrosplenial cortex
- Area 30 – Subdivision of retrosplenial cortex
- Area 31 – Dorsal Posterior cingulate cortex
- Area 32 – Dorsal anterior cingulate cortex
- Area 33 – Part of anterior cingulate cortex
- Area 34 – Dorsal entorhinal cortex (on the Parahippocampal gyrus)
- Area 35 – Part of the perirhinal cortex (in the rhinal sulcus)
- Area 36 – Part of the perirhinal cortex (in the rhinal sulcus)
- Area 37 – Fusiform gyrus
- Area 38 – Temporopolar area (most rostral part of the superior and middle temporal gyri)
- Area 39– Angular gyrus, considered by some to be part of Wernicke's area
- Area 40 – Supramarginal gyrus considered by some to be part of Wernicke's area
- Areas 41 and 42 – Auditory cortex
- Area 43 – Primary gustatory cortex
- Areas 44 and 45 – Broca's area, includes the opercular part and triangular part of the inferior frontal gyrus
- Area 46– Dorsolateral prefrontal cortex
- Area 47 – Orbital part of inferior frontal gyrus
- Area 48 – Retrosubicular area (a small part of the medial surface of the temporal lobe)
- Area 49 – Parasubicular area in a rodent

- Area 52 – Parainsular area (at the junction of the temporal lobe and the insula)

(*) Area only found in non-human primates.

The VoxelNET system is capable of representing the voxelised volumetric structure of the brain corresponding to the Brodmann areas in the form of a material voxel structure, as well as the voxelised spatial environment providing the perceptual, physical context of brain activations and the neural/cognitive functions that they represent (see figure 4). This can provide a much more ecologically valid method of studying neural function that the rarefied experimental structures more typically used in cognitive and neural sciences.

VI. Parallel Processing and Quantum Computing

To be able to process vast amounts of data, parallel processing or parallel computing is a method of simultaneously breaking up and running program tasks on multiple microprocessors resulting in reduction of processing time. Large problems can often be divided into smaller ones, which can then be solved at the same time and not sequentially. As an example: we may gaze into the world and direct attention towards complex scenes and need to calculate both optical sensors input and other operational calculations at the same time. A 3D infrastructure such as VoxelNET can be used to subdivide and direct computing to save/distribute computational resources while also displaying information/parts of scenes. Parallel processing can be accomplished via one computer with multiple cores and expanded via a computer network.

A. Quantum Computers, Quantum Computing and Quantum Computational Intellgence

Quantum computers aren't limited to two states; they encode information as quantum bits, or qubits, which can exist in superposition. Qubits represent atoms, ions, photons or electrons and their respective control devices can work together to act as computer memory and a processor. Quantum computing is a non-classical model of computation. Whereas a classical computer encodes data into fundamental units called bits, where each bit represents either a one or a zero, a quantum computer encodes data into bits that can represent a one, a zero, or some combination.

a. Quantum Qubit

A qubit, Qubit or Qbit, see Figure 7, can have 2-bit states at the same time. Therefore, a qubit is equal to a bit, but also equal to 2^Q bits. The two most relevant aspects of quantum physics are the principles of superposition and entanglement. A Qbit can be thought of as an electron in a magnetic field.

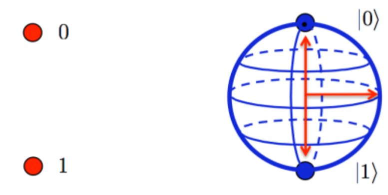

Figure 7. A classical bit and a Quantum Qbit comparison.

The 'Bloch sphere' is a geometrical representation of the pure state space of a two-level quantum mechanical system (Qubit), named after the physicist Felix Bloch, see Figure 8.

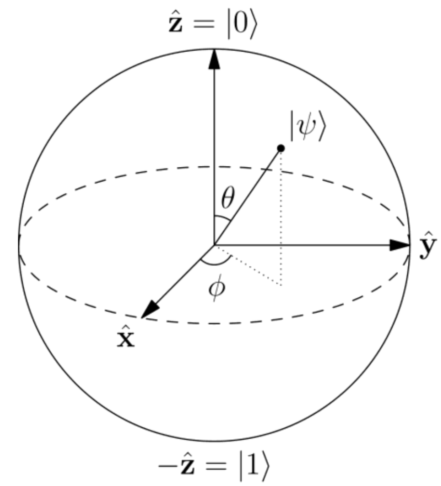

Figure 8. The quantum Bloch sphere, a geometrical representation of a quantum state space.

The bottom line of Quantum Computing (QC) is the existence of correlations between different Qbits as superposition states which when destroyed by measurement or any other means, the proper correlation is instantaneously communicated between the Qbits. Researchers have proposed some models where the neuron is modeled like a Qbit and organized into networks in the form of Quantum Associative Memory (QAM).

Here in regard to VoxelNET, we suggest that the indexed voxels can compute content in a discretized, quantized and spatially distributed way and therefore function as a quantum computational infrastructure. Every voxel can include one or several bloch spheres for computation purposes.

The interest in QC -physically based computation founded on quantum-theoretic concepts - has grown since the early 90's in the computer and cognitive sciences as a result of claims by Deutsch [23] 1985, [24] 1989 and Shor [25] 1994 that problems regarded by computer scientists as NP-hard or NP-complete can be solved by a quantum computer. [26] "Since it is regarded that if a computational solution can be found to one of the problems in the NP-complete class then a solution can be found to all problems in this class. These claims raise deep questions for computer scientists as to the nature of computational and algorithmic processes as well as the relation between computation and physical processes. Penrose [27] claimed in 1994 that solving the quantum measurement problem is a prerequisite to understand the human mind, and Hameroff's [28] proposal the same year that consciousness emerges as a macroscopic quantum state from a critical level of coherence of quantum-level events in and around cytoskeletal microtubules within neurons, raise important questions for the scientific foundations of cognitive science and the appropriate level for a computational account of mind/brain [29].".

An exhaustive survey made in 2012 [30] included various applications of Quantum inspired Computational Intelligence (QCI) techniques and proposed to lay out the landscape for researchers on Quantum computing as a young discipline. The introduction lays out "Computational Intelligence (CI) as an offshoot of artificial intelligence which involves the study of adaptive mechanisms to enable or facilitate intelligent behaviors in complex and changing environments. CI consists of collective efforts in emerging, fundamental computational paradigms, unlike intelligent systems (IS), which covers all aspects of artificial intelligence (AI) and focuses on the development of the latest research into practical, fielded applications. CI depends upon numerical data supplied by manufacturers and does not rely on "knowledge". AI, on the other hand, uses knowledge derived from human experts. The knowledge or intelligence exhibited from CI is self-emerging and spontaneous as opposed to manmade and artificial from AI.".

The theory of QC is related to a theory of reversible computing, which brings together ideas from classical information theory, computer science, and quantum physics.

Mapping brain regions and running a variety of Neural Network (NN) methods such as Back Propagation NN, Training Algorithms, Hamiltonian NN, Hopfield NN, Self-Organizing Map, Radial Basis Function NN, Recurrent NN, Stability Analysis, Support Vector Machines, Spiking NN, Quantum Inspired Fuzzy System, Quantum Inspired Evolutionary Methods must be based upon systemizations of environmental, human and robotic action, sensor data and computational power so that the background world representation is sufficiently systematic to support synthesis or comparison of CI results.

VII. CONCLUSION

This paper has presented a number of functions for which integration has been based upon a coherent unifying system of spatial and volumetric indexing and representation. The paper has emphasized the particular relevance of representing both the spatial structure of the physical world and that of neural information processing in order to study and leverage the response of human cognitive/neural systems to external situated 3D structures and events. The use of a unifying 3D location voxel structure has also been considered as a framework for managing computation on a spatial basis, where computing load can be managed and distributed on a spatial volumetric basis, and also potentially support quantum computing.

The overall conclusion is that 3D spatial structure is inherent in many kinds of data, information, knowledge and processes, and this can be used to integrate and coordinate distributed processes having diverse primary functions. The current internet, based upon abstract links and document-style interfaces, does not intrinsically provide this kind of coherent 3D spatial structure.

The main author and her 4D Internet team are currently implementing and progressing VoxelNET from Technology-Readiness-Level (TRL) 4 to 6 and next year (2021) progressing it further towards TRL 7-8.

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