<u>From Geometrical Foundations of NN Research to Lead-Roles in Silicon Valley Information Industry in Flight Control and Infohighway Interface</u>

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From Geometrical Foundations of NN-Research to Lead-Roles in Silicon Valley Information Industry, in Flight Control and Infohighway Interface

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Abstract - **"Information geometry" is heralded as the mathematics of neurocomputing, thus should discern the intrinsic language of neurocomputers from biological neural nets. The effort to lead neuroscientists to the unfriendly path of tensor geometry is remembered, neurobiological evidence supporting axiomatic geometrical neural net theory is recalled and relevant questions for dialogue between neuroengineers and neurobiologists are listed. Because neurocomputing became industrialized, focus is now on applications benefitting from the geometrical approach. Two extreme manifestations of neural geometry stand out in Silicon Valley information industry applications. Flight control, by NASA Ames Center, uses cerebellar neural nets which evolved in nature to flight-enable terrestrial species. Flight is a trajectory in the spacetime manifold, and the cerebellum as internalization of spacetime metric into a neural net is existence-proof of solution. Infohighway-interfaces, another focus of Silicon Valley information industry, use non-metrical (e.g. fractal) geometries that open avenues to image compression, speech and character-recognition by NN.**

1 Introduction: the Trend towards Neural Geometry

About a decade after expensive pioneering [1],[2],[3] when at the time of taking risks a"geometrical approach" was fiercely opposed [4], these days "information geometry" is heralded as the mathematical discipline of neurocomputing [5] - conspicuously even by its early opponents [6]. Fig.1. below shows this "evolution" towards geometry as "neuromathematics". An overview of the unquestioned turn towards neurogeometry was given at the turning point [7].

2 The Nature of Neural Geometry

If "neuromathematics" or "information geometry" is a genuine discipline, than the thesis of this author is, that it must discern the intrinsic mathematical language of neurocomputers from actual biological neural nets. Thus, after the "geometry-approach" unfolded, emphasis was first focused on neurobiological demonstrations of the fundamental axiomatic deviation from "Euclidean geometry", erected by Cartesian frames of reference. In an array of papers, the vestibulo-cerebellar biological neural networks were mathematically described in term of tensor geometry [8], [9], [10] and it was demonstrated by co-workers [11] as well as by independent experimental neurobiologists [12] that the tensor-approach is one of the few neural net theories that both poses experimentally testable paradigms, as well as the paradigms are experimentally confirmed. "Sensorimotor neurobiology", and especially its leading area of "vestibulo-cerebellar systems and gaze control", once took off from Euclidean geometry towards the difficult path of tensor geometry, will never be the same again, most certainly could never revert to linear systems theory as borrowed from control engineering. Yet, for some time neuroscience may not be ready to squarely face the challenge of experimentally finding out the true nature of "neural geometry".

The problem is not only that new mathematical axioms are extremely difficult to accommodate (i.e. to accept the non-Euclidean nature of neural geometry, such that mathematical "brain vectors" are not points in a linear vector-space, but come at least in co- and contravariant, or even in mixed vectorial forms). A second challenge is that experimental avenues towards revealing "neural geometry" are unconfortably unpaved. A third challenge is that it is already evident that neural geometries do not stop at gently deviating from Euclidean geometries - e.g. that orthogonal Cartesian frames could be experimentally demonstrated in the vestibular system as patently non-orthogonal, general coordinates. As Figure 2. demonstrates, the vestibulocerebellar system provides anatomical evidence both for the fact that vestibular semicircular canal systems represent non-orthogonal generalized frames of reference -- erecting metrical geometries with their metric tensors deviating from the Kronecker-delta of Euclidean spaces —, but also for the fact that the main neurons of the cerebellar cortex, the Purkinje cells display a fractal neural geometry [13].

Each of ~~the~~ two extremes, metrical Riemannian (locally Euclidean) neural vectorspaces as well as grossly non-metrical fractal neural geometries, however, clearly open avenues both for experimental discovery, then mathematical characterization, and also for application of neural geometries in major information industries, e.g. those leading in Silicon Valley.

3 Experimental-Theoretical Dialogue: Discovery of Neural Geometries

3.1. Experimental investigation of metrical neural geometries

As originally introduced [14], see Fig. 2., the so-called multi-unit recording technique provides both an opportunity

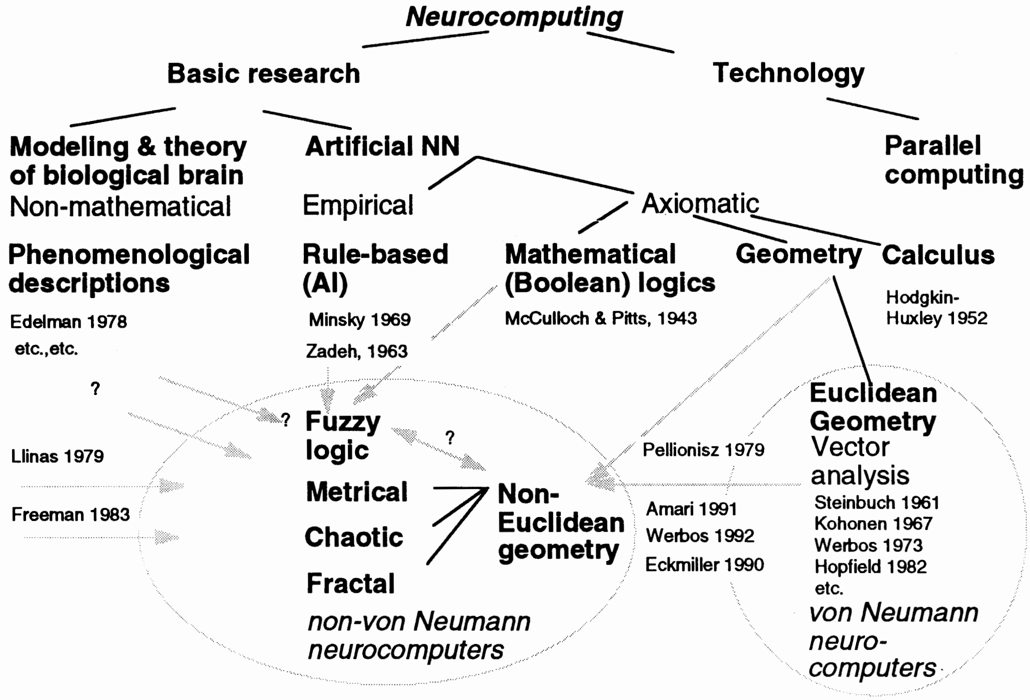


Fig. 1. Main evolutionary lines of the trend towards geometry as the discipline of "neuromathematics". Two most important axiomatic departures are shown here as the break from mathematical logics, and the break in 1979 from Euclidean geometry towards metrical and non-metrical, non-Euclidean geometries. One of the most interesting challenges for the future is a unification of fuzzy logic and non-Euclidean geometry.

and a need for a geometrical analysis. While processing multielectrode data is most commonly a correlation analysis [15],[16],[17], about a decade ago the geometrical approach was taken [18] proposing an interpretation of neuronal activities of n neurons as a point in the n-dimensional vectorspace in which a Euclidean geometry governs.

It was, however, pointed out immediately, [14], see Fig.2., that instead of the automatic assumption of a Euclidean metric tensor of neural n-spaces (on which calculation of geometrical features, such as distances, would be based) the approach needs to be reversed. Geometrical analysis of multi-unit data cannot start with a well-defined geometry (since it is basically unknown). Instead, the multielectrode analysis method must be the means of resulting in a geometry as discerned from experimental data. This appeal was well taken by the community concerned with multielectrode recording techniques, since it is readily accepted that the assumption of Euclidean geometry is arbitrary – however, for some time no specific experimental paradigm was forwarded to offer a concrete procedure to define the geometry (measure the metric tensor) of the neural n-space.

A cooperative project led to an experimental paradigm by which the geometry (metric tensor) of the neural n-space underlying vestibular and cerebellar functional spaces can be quantitatively established. Tensor network theory predicts that the cerebellar input (intercepted at the level of cerebellar Purkinje cells) is a covariant (sensory-type) intention-vector. In case of such covariant vectors the cross-correlogram table of firing frequencies converges to the covariant metric tensor, from which the contravariant metric can be calculated by the Moore-Penrose generalized inverse [19]. This procedure of multi-unit data analysis, therefore, yielded in an experimental collaborative study [20] a specific measure of both metric tensors of the neural n-space, by which the internal geometrical representation of external physical invariants could be appropriately calculated. The experimental evidence revealed that (a) the neural geometries intrinsic to cerebellar transformation are non-Euclidean (Riemannian), (b) the cerebellar neural geometry changes in response to changes in the external physical geometry of the motor apparatus (a geometrical re-definition of cerebellar "learning").

3.2. Experimental investigation of fractal neural geometries

There is in recent times an "explosion" in discovering nature's geometries, pointing far beyond metrical manifolds [21]. Evidence rapidly gathers that grossly non-Euclidean fractal and chaotic geometries are also manifest on neurons

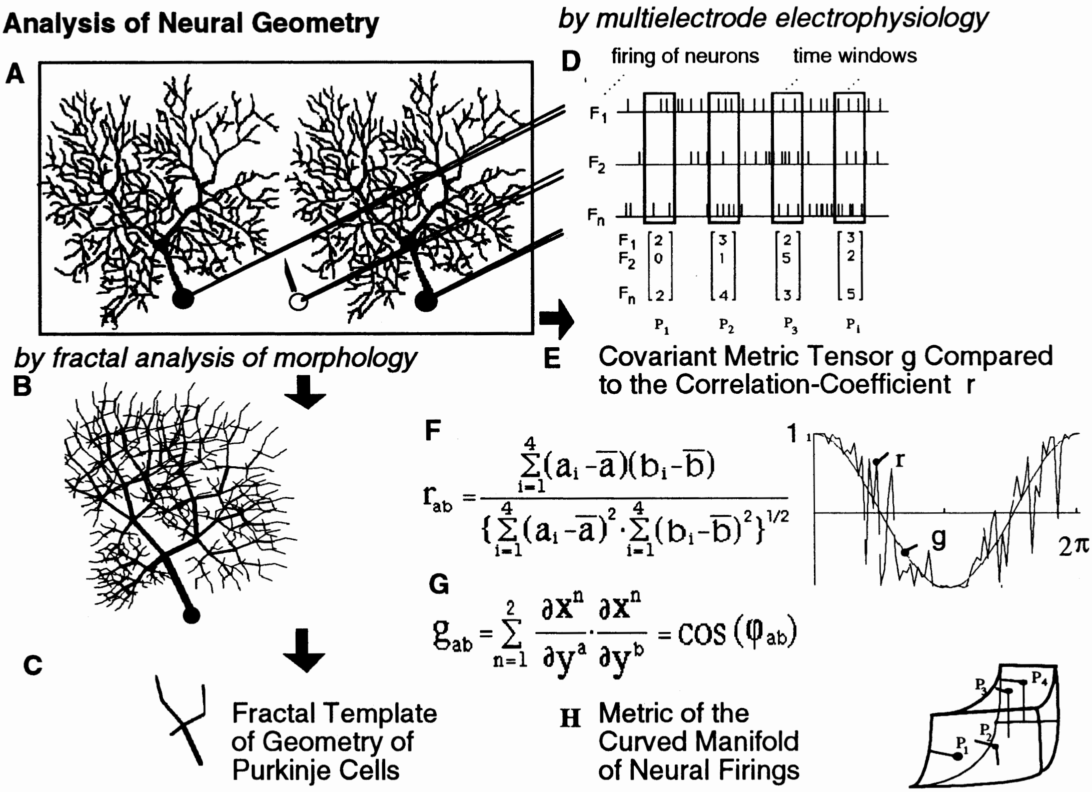


Fig. 2. Cerebellar neural nets reveal both a metrical functional geometry - but with non-Euclidean metric (H) and a non-metrical (fractal) structural geometry (of the Purkinje cells). Details in [13]

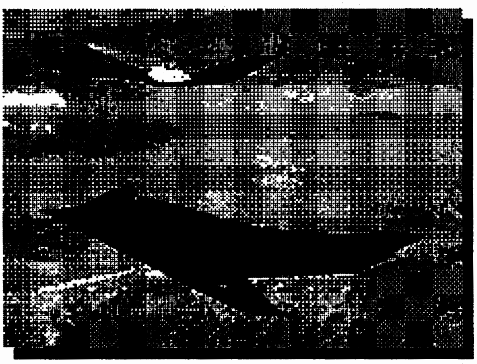
and neural systems [22],[13],[23]. These developments mandate a massive effort to ensure that neurocomputer theory and development goes beyond the stage of vector-matrix notation assuming Euclidean geometry of the vectorspace. As outlined earlier [24], similar to earlier advances in brain theory, progress is hinged on an interaction of experimental neuroscience in discovering the nature of such geometries and simultaneously of theory of neural nets in appropriately using such understanding.

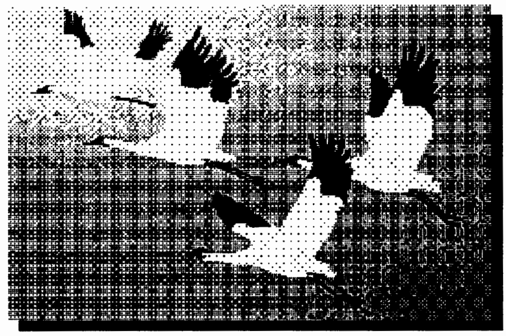
Some impact of the use of generalized vectors on the fields of research of association and pattern recognition is already clear [24] as these categories are rather squarely based on the concept of "distance". Vector formalisms of theories of association and pattern recognition are likely to be rejuvenated by the use of generalized vectors once the underlying metric tensor becomes experimentally accessible. This, in a general sense necessitates a re-thinking of pattern recognition, which customarily starts with considering n-tuplets as points in regular vectorspace separated by Euclidean distances [25].

A geometrical re-thinking of pattern recognition is also under way in an even more radical sense than allowing "pattern vectors" to be generalized. As Fig. 2A-B. illustrates, the complexity of the dendritic arbor of Purkinje nerve cells can be rather closely approximated by deterministic fractal geometry. It is noteworthy that the complex tree (Fig.2B) is fully determined by the fractal template (Fig.2C). Thus it appears that neural systems do use a fractal geometry for information compression, e.g. at least in the morphogensis, if not in information processing of brain cells. Remarkably, in technological research and development fractal geometry already found its way to utilization in image compression [26]. The above facts taken together trigger the germinal idea exposed for the first time in [7] that neural systems utilize a fractal geometrical information compression in (visual) recognition of patterns, especially of textured images. This idea is obvious in the sense that there is no philosophical reason to limit the brain to the use of Euclidean geometrical primitives in vision [27]. A specific suggestion in [7] following from the above idea was to experimentally probe the visual system fractal geometrical primitives. Testing the visual system by fractal geometrical primitives (beyond Euclidean primitives such as points, line segments and directions as it was done in the classical studies by [28]) is prone to become a new approach in experimental-theoretical investigation. If the role of the CNS is to reflect, by an internal geometrical model, the external geometry, it does not escape one's attention that fractal textures have a natural and pleasing appeal to our brain [29].

4 Applications of Metrical Neurogeometry in Flight Control, and Fractal Neurogeometry in Information Superhighway Interfaces

NEURAL NETS





Neurocomputer=
AeroSpace Computer

Neurocomputers are the AeroSpace computers of the future (gracefully degrading, massively parallel, adaptive software)

NEEDED: access to both biological prototypes of neuro-computers (natural cerebellar neural nets) and real-life applications (sensorimotor, flight control tasks) for which Nature developed neurocomputers

Fig. 3. Concept-diagram of neural nets as flight-controllers, presented in 1992 IJCNN in Baltimore [33] and in Sept. 1992 to the Research Council of NASA Ames Research Center.

4.1. Application of metrical cerebellar neural geometries in flight control

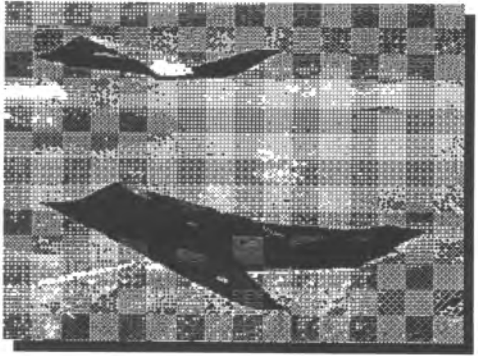
This paper, overviewing the scientific trend towards "neural geometry", showed that (1) multielectrode experimentation reveals how non-Euclidean distances in neural functional spaces can be calculated to measure external (physical) invariants by internal generalized coordinates, (2) introduction of such generalized vectors leads to new avenues in the theory of pattern recognition and association, (3) regarding non-metrical neural geometries, it is shown that morphology of single neurons reveals a fractal geometry, (4) in turn, the existence of such "fractal templates", that comprise complexity, leads to the introduction of the concept that visual recognition of complex patterns and textures by the brain may be based on fractal geometrical primitives rather than customary Euclidean templates (such as points, lines, spheres and cylinders).

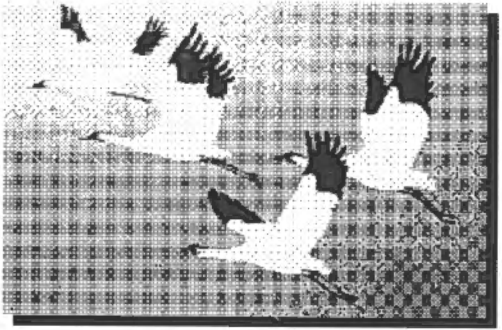
Given the fact, however, that in the past decade neurocomputing became also an industry, not just a new interdisciplinary science, the paper finally turns now also to industrial applications directly benefitting from a geometrical approach to neural nets. Characteristically, both extreme manifestations of neural geometry, metrical and non-metrical, find their ways to crucial applications in Silicon Valley information industry. With NASA Ames Research Center in the heart of Silicon Valley, reorganized around "information Systems", it is no surprise that an important application, seeded in 1992, surfaced with a "Neural Nets for Aircraft Control" Symposium in the summer of 1994 [30]. As shown by Fig. 3, just as cerebellar neural nets were used in evolution by nature to flight-enable terrestrial species, artificial (cerebellar) neural nets will be needed to flight-enable those aircrafts that were built not for flight, but e.g. for radar-invisibility, and thus have extreme difficulty in flying without on-board advanced avionics. Precursor of this application, elaborated in [31] (and first public display of Fig.3.) was at the 1992 IJCNN at Baltimore. The two collaborative papers in its proceedings [32], [33] laid down the foundation for the convergence of backpropagation adaptive critique and tensorial geometrical cerebellar models, and with MacDonnell-Douglas, Boeing and Lockheed engaged at this time [30] it is expected that aircraft control by neural nets in projects at US and overseas aerospace firms will conclude that the existence-proof of flight control by biological cerebellar neural nets provides a solid basis for leading-edge industrial applications.

4.2. Application of non-metrical neural geometries in information-superhighway interfaces

Given the fact that flight is a trajectory in a metrical (spacetime) manifold, where a key concept is how the functional geometry of the governing neural network dynamically embeds the physical geometry into a constantly accommodating physical geometry of the flying instrument, it is natural that the Metaorganization-principle of homeometric

NEURAL NETS





Neurocomputer=
AeroSpace Computer

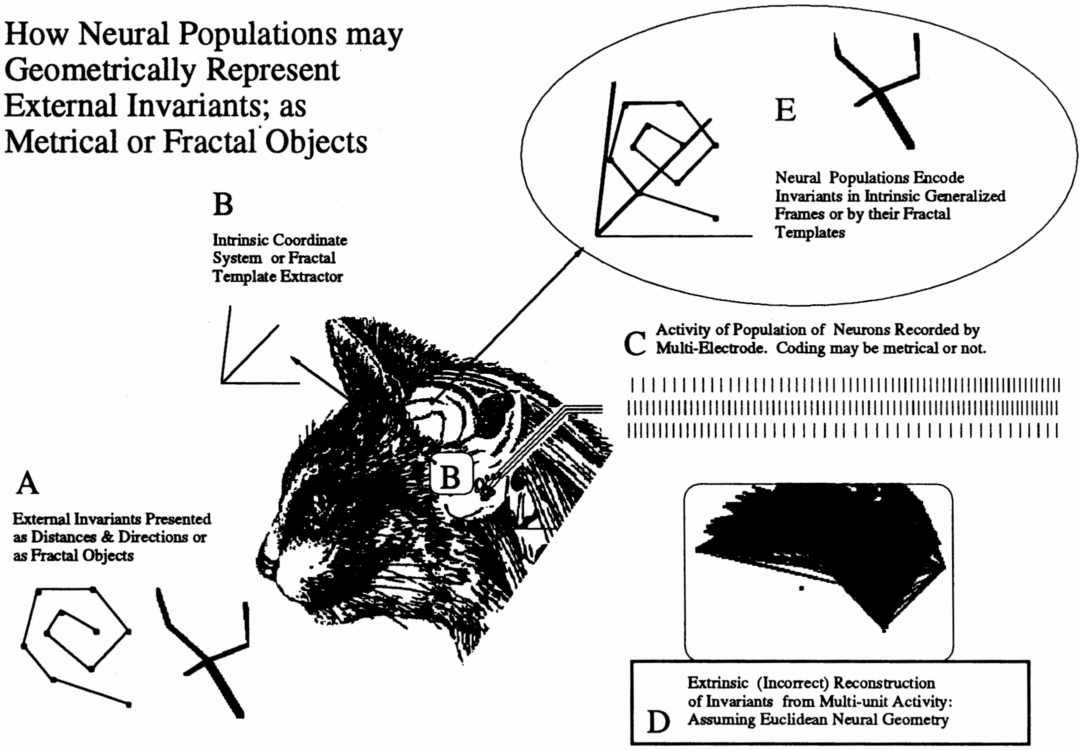


Fig. 4. External invariants can be interfaced by neural nets to the superhighway of "nerves" either as metrical, or non-metrical (e.g. fractal) geometrical objects. Principles and advantages are vastly different.

spaces is one of the general neural net theories that come into play in flight control.

It is interesting, however, that in another key NN application in Silicon Valley information industry, in "information-superhighway interface" development and manufacturing, precisely the opposite, non-metrical neural geometries are likely to play a key role.

Indeed, the "information superhighway" initiative in the USA poses two technical challenges (in addition to the massive political, financial, organizational and even cultural challenges inherent in the initiative). One (by far the easier) challenge is to lay down the wiring by fiber-optics, the "nerves" of the body of USA (already partially accomplished by telecommunication concerns). This, just as laying down the nerves connecting all body-parts to a central processor (brain) in a biological system, is relatively simple, and requires no "neural networks" in the complex sense. A different, and a staggering, challenge however (exactly the same way as in biological systems), is to interface the "wiring" to the external world, i.e. via retinal-, cohlear-, collicular- and olfactory (etc) neural nets that not only connect the wiring system with the world but establish the (non-trivial) principles of its geometrical representation.

A symbolic presentation of the problem is shown in Fig. 4., where objects of the external world are internally represented by an encoding-interface. It is clear, however, that simple objects (geometrical primitives) could be seen either as composed of metrical elements, where a sequence of distances and directions must be encoded, or — alternatively— e.g. visual objects— could be "seen" as fractals, where the task is to extract the fractal template e.g. from a texture and to transmit the template instead of the texture, thereby achieving an immense bandwith-reduction.

Although presently only the visual (image-compression) aspects of "information-superhighway interfaces" are tackled and speech-recognition, handwritten character recognition and other fields are still largely untouched by non-metrical geometrical representation theory, in an industrial environment of companies where "survival of the fittest" depends on the potency of neural net engines used in particular interfaces, the future will bring an utterly exciting and economy-driven rush towards the science of such non-trivial "neural geometry representation theories".

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