Neural Networks of the Brain: Their Analysis and Relation to Brain Images

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***Abstract*— We develop a mathematical framework of continuum neural field theory as the beginning point for an analysis of the multi-modular global brain. Applications to cortical dynamics and learning in somato-sensory cortex, visual cortex and motor control are briefly reviewed. Extensions to a broader range of brain systems, including attention and emotions, are outlined. A deduction of structural equation models for the coupled neural modules is then briefly noted, with all neural variables acting as hidden variables in a well-defined manner.**

I. INTRODUCTION

The brain is a complex dynamical system, as observed at all levels of its investigation: from overall dynamics of the global brain down to the functioning of synapses, in which a wealth of different neuro-chemicals are involved. However there is a difference between modelling the system at the micro-processing level of the brain in comparison to at the global level. The former involve systems of variables more controllable than in the global case, as are the possibilities of testing predictions of models. That is even possible at a higher level, as for example in recent careful .bottom-up. models of the cerebellum in its role in conditioned learning [1]. However such features are not so clear for the global brain.

There are only few detailed models of the dynamical interactions of modules across the vast reaches of the brain. Even these tend to be based on simulations, and not any mathematical principles. In this paper we propose a program to lift our modelling and analysis sights higher to the global brain. We do that in terms of recent functional proposals for overall control systems in the brain: of attention [2], [3], of motor control [4], [5], of emotions [6], [7], and even of consciousness [8]. We also discuss how to relate the results of such an approach to the plethora of data on the networks of the global brain now pouring in from brain imaging.

To advance in this task of analysing the global brain, we have to consider the level we will use to model it. Do we take it lobe by lobe, or module by module, column by column, or neuron by neuron, or even down at synaptic level, or even lower at molecular level? The principle I propose is to start with the simplest sorts of components (graded neurons), and try to determine what these could achieve. I will use functional guides coming from control theory to indicate how different modules could function together, either in attention, motor response or in emotion processing. There is now a vast amount of information coming from brain imaging. I will also consider the important question of how to relate in principle the neural model I will analyse to this information.

This program is started in the next section, where I present the basic components. This is then formulated in detail mathematically in the following section, along with some analytical results. A control version is then developed in section 4. A brief summary of results is given in section 5. The possible relation to brain images is considered in section 6. Conclusions and open questions are presented in section 7.

II. THE BRAIN’S BASIC COMPONENTS

There is a hierarchy of complexity in the global brain. If each complexity level was modelled faithfully we would have enormous complexity of the overall system by the time we arrive at describing the global brain itself. One way to proceed is by simplifying the problem to one which looks as if it has a chance of being solved. Further additions of complexity, would regain the brain in all its complexity, in the process having some idea of what the principled powers were of the basic ‘first approximation’, and what further powers are needed, and might be added.

The first step. of formulating the basic or simplest approximation.should be so structured as to lead us to expect interesting features that would lead to explanation of some of the true powers of the brain in reality. But step must be simple enough to be relatively soluble.

A first approximation which has drawn considerable interest recently, but only at the single (or few) module level: continuum neural field theory (CNFT). One pioneer of this was Amari [9] who proved in 1977 some remarkable features of a certain class of CNFT in 1-dimension: the existence of long-term localised solutions, or .bubbles. of restricted neural activity. This was extended more recently to the 2-dimensional case [10]. A little later Amari and colleagues developed a mathematical analysis of learning of afferents in the CNFT framework, in terms of the distribution of inputs [11]. That has since been applied to the brain in a variety of ways: showing the development of orientation selectivity in a structured form in V1 [12], explaining various illusion in visual perception [13], the unmasking features of somato-sensory cortex when certain components of the inputs were damaged (and agreement obtained with experimental results on this unmasking) [14], [15], various applications to psychological experiments [16], and more recent applications in motor control [17], [18], [19], among many items.

All of these applications show the value of CNFT for modelling local processing, by single modules, in the brain. I extend this approach to the framework of global brain processing, initially by taking hard-wired interacting CNFT modules representing a simplified brain, and attempting to solve the resulting dynamics, or at least obtain general features of this dynamics. The next step is to include learning, as done by Amari and his colleagues in their move from dynamics [9] to afferent learning [11], and as extended to the two-dimensional case in [10].

III. MATHEMATICS OF THE SIMPLE BRAIN

A CNFT model is based on the approximation of a module of neurons as composed of a two-dimensional sheet of neurons, with the neuron at position **r** on the sheet having membrane potential V(**r**).

The dynamics of the neurons is simplified by assuming a graded response pattern for each neuron output (although extendable to spiking neurons if needed). Thus the output spike frequency of each neuron is some function f( ) of its potential; the simplest case being a step function, although results have been obtained for more general sigmoid functions. The simplest dynamics is taken as:

$$\tau \frac{dV(\mathbf{r})}{dt} = -V(\mathbf{r}) + w * f(V)(\mathbf{r}) + I(\mathbf{r}) - h \qquad (1)$$

where I is the external input to the module at that point, $w(\mathbf{r}, \mathbf{r}')$ denotes the lateral connection strength between the neuron at $\mathbf{r}'$ and that at $\mathbf{r}$, -h is a constant inhibitory bias to all neurons to assure stability and suitable competition between neurons, and $*$ is the usual symbol for the convolution product taken over the positions of the module.

The cortex can be represented, to a first approximation, by a set of different two-dimensional sheets of neurons coupled to each other, these modules being differentiated by the thickness of their cortical layers, sorts of neuromodulators, separate function being performed (as a map of the body surface or visual field for example). We therefore extend (1) to a set of interacting modules as:

$$\mathbf{T} \frac{dV(\mathbf{r})}{dt} = -V(\mathbf{r}) + W * f(V)(\mathbf{r}) + \mathbf{I}(\mathbf{r}) - H \qquad (2)$$

where the extension of (1) to (2) is achieved by taking V to be a vector-valued field of membrane potentials (each component denoting the neural field for a given module), $W(\mathbf{r}', \mathbf{r})$ now denoting the matrix of field connections, with diagonal connections being the lateral ones entering originally in (1), the off-diagonal ones being those connecting different modules, -H is now a diagonal matrix, with constant values in each entry for a given module although with possible differences across modules to allow different levels of overall inhibition, and **I** denoting a vector field of external inputs, each component again being associated with a given neural field module; the matrix **T** denotes a diagonal matrix of time constants (where also in (1) this can be extended to different time constants for different neuron positions if so desired). We are simplifying by taking the same co-ordinates for each module; again that can be generalised. Further we are only taking neurons of the same type in (1) and (2); again that can be extended to those of inhibitory and excitatory form or of different sub-populations, by suitably extending the notation in these equations.

We now indicate some of the features expected from (2), extending those possessed by (1) – bubble existence, dynamics of bubbles, learning structures.

1) Basic Features of the Dynamics
   A Liapunov function can be derived for the dynamics of (2) extending that for (1) in the case of symmetric connection matrix W (across modules as well across the lateral connections in each module), as in [17], thus providing general stability arguments.
2) Existence of Bubbles
   The one- and two-dimensional bubble analyses of [9] and [10], and the many simulations in the references [12]-[19], lead to the expectation that there will exist multiple bubbles, across a range of modules. It is possible to develop equations for coupled bubbles from (2); that will be described later. These bubbles of activity allow both for dynamical effects to occur, as well as learning processes to arise (see point 4) below that are highly relevant to real brain processes, as [12] - [19] indicate: in the generation of orientation sensitive neural structures similar to those in V1 [12], to help explain illusions by suitable bubble activity [13], to describe reorganisation of somatic maps in monkeys under destruction of sources of inputs [14], [15], to explain saccade generation in colliculus [16], or to model motor control [17], [18], [19].
3) Dynamics of Bubbles
   Bubbles have been found [9] - [19] to be driven to flow to regions of highest input. A similar situation is expected to occur for the coupled bubbles in the expanded version (2) of CNFT, as will be described later.
4) Learning Structures
   The original one-dimensional work of [11] was extended in [10] to two dimensions and to applications to specific brain modules in [12] - [19]. The most crucial feature of this study was the presence and exploitation of instability in the learning law dynamics, producing discontinuous periodic structures mapping higher dimension input spaces down to the two-dimensional sheet in a clearly defined, even analytic, manner. Similar structures are to be expected in the extended case of (2).

It is clear that the module-based structure of (2), containing as it does an inherent similarity to the cortex, is of great value to obtain extension to the hierarchy of modules of the results such as those obtained in [9] - [19], as any summary reading of these papers would show. This is especially so for those results which depend crucially on the Mexican hat structures used in detailed simulation of psychophysical results [12] - [19]. If we had moved to a .squashed; framework (all modules put together into a single one) , however, we lose the transparency needed to extend the various results of [9] - [19] from a single module to a hierarchy of such modules. Thus we would not expect it will be easy to prove, in the squashed representation, the results of, say, the existence of locally bounded ‘bubbles’ [9], [10], [16], [17], [18], [19] coupled across various modules, although in general with different sizes, or of the development, through Hebbian learning, of suitably periodic structures of afferent weights from one module to the next in the original hierarchy (as known experimentally, although with increasing wavelength in going from V1 to V2 to V4 and so on [22], especially fig 24.6 in that reference). Nor will the detailed properties of these solutions be easily derivable. This is due to the loss of the ability to extend all of the elegant properties of solutions of (1) upwards in the hierarchy by means of the transparency of the structure of (2) when working in the far less intuitively understandable squashed multi-modular system being considered as an alternative.

A final general point about the structures of (1) and (2) is concerned with the inhibitory bias, which arises as the inhibitory constant fields arising from the constant h in (1) or its extension to the diagonal matrix H in (2). These have a strong effect, as any reading of the papers of [9] - [19] indicate, in association with the existence of bubble solutions and periodic unstable afferent connection strength learning equations. The constant(s) could be absorbed into the definition of the potential $V(\mathbf{r})$, but again this hides the meaning ascribed to V as corresponding to a local, laterally connected field, vanishing at infinity. This is all part of the general structure of the CNFT approach, as more fully described in [9] - [19].

Let us consider how the structure given by (2) can be used to extend some of the specific results of (1). We consider 2 modules only, as has already been considered in [13] in the case of colour illusions, involving two colour modules, one for each colour, and the bubble solutions found to fit the patterns observed when a blue/red boundary was stabilised on subjects. retinas (one being the non-intuitive ‘sea’ of blue and red mixed together, as experienced by some subjects). In the asymptotic limit in time, (2) becomes:

$$\begin{aligned} u(x) &= \int W(x-x')f[u(x')]dx' \\ &+ \int W'(x-y')f[v(y')]dy' + h \\ v(y) &= \int W''(y-y')f[v(y')]dy' \\ &+ \int W'''(y-x')f[u(x')]dx' + h' \end{aligned} \tag{3}$$

where we have assumed translation invariance of the interconnection matrices, and the variables x, etc denote suitable co-ordinates on the cortical surface. In terms of the standard notation [9], [10], and defining the function:

$$U(x) = \int_0^x W(y)dy \tag{4}$$

we can rewrite (3), for a local ‘double bubble’ solution, with x restricted in the interval [a, b] and y in interval [c, d], as

$$\begin{aligned} u(x) &= [U(x-a) - U(x-b)] \\ &+ [U'(x-c) - U'(x-d)] + h \\ v(y) &= [U''(y-a) - U''(y-b)] \\ &+ [U'''(y-c) - U'''(y-d)] + h' \end{aligned} \tag{5}$$

where

$$u(a) = u(b) = v(c) = v(d) \tag{6}$$

Applying the constraints (6) to (5), we obtain an extension of the set of equations (7) of [9], as

$$\begin{aligned} 0 &= h + U(b-a) + [U'(a-c) - U'(a-d)] \\ 0 &= h + V(b-a) + [U'(b-c) - U'(b-d)] \\ 0 &= h' + U'''(d-c) + [U''(c-a) - U''(c-b)] \\ 0 &= h' + U'''(d-c) + [U''(d-a) - U''(d-b)] \end{aligned} \tag{7}$$

The equations (7) can be investigated for coupled ‘bubble’ solutions, and these can be found, as can extension of the theorems of [9] on the nature of these solutions (as also discussed in [13]).

The system of equations (5), and the time dependent form of equations they arose from in (2), can also be analysed for stability, by using a first-order perturbation approach. The basic result is the coupled equations (in a set of coupled module indexed by i, j):

$$\begin{aligned} \frac{d\Delta_i}{dt} = \frac{1}{\tau_i}[\frac{1}{c_{i1}} + \frac{1}{c_{i2}}\{[\Sigma_i W_{ij}(x_{i2} - x_{j2}) \\ -W_{ij}(x_{i2} - x_{j2})] + h_i \\ -[\Sigma_i W_{ij}(x_{i1} - x_{j1}) - W_{ij}(x_{i1} - x_{j2})]\} \end{aligned}$$

where $\Delta_i = x_{i2} - x_{j1}$ is the width of the bubble in the ith module, and $c_{i1} = \delta \mathbf{u}_i(x_{i1}, t)/\delta t$, and similarly for c_{i2}. These equations extend those of stability in [9], allowing determination of the stability of bubbles and their movement in the presence of new inputs, in the coupled module situation. More detailed results will be reported elsewhere.

IV. INSERTION OF CONTROL STRUCTURES

So far we have only extended the standard CNFT model of a single module to that of several such modules, without understanding how functional differentiation can be included in the system. We now turn to that important aspect. To justify our approach we need to accept that we cannot expect our extended model to learn its feed-forward and feedback connections all on its own, without any use of genetic memory. This was built up over hundreds of millions of years by pressure of the environment, which is changing all the time. Such pressure has led to crucial functional variations between modules, that allow them to be functionally differentiated into input processing modules, semantic map modules, higher level control modules and response modules, as well as others (and also with differentiation at sub-cortical level). This differentiation is assumed to have some genetic basis.

The first and fourth of these types of modules have already been discussed in the brain context in [12] - [19]. Here we turn specifically to the third class of modules, those for attention control, by suitable assumptions on the lateral connection matrix W in terms of the depth, strength and width of the lateral connection matrix internal to a module, as well as by temporal flow of activity. The connection matrix elements affect the size of bubbles, and the overall level of the WTA nature of the module. The higher level modules in parietal lobe will therefore be allocated large values of inhibitory connections so as to provide a strong bias towards competition and hence generation of attention control signals.

The temporal flow of activity of the brain has been observed in many ERP studies. It is observed that early input flows through low-level sensory cortices rapidly to prefrontal cortex, and thence is used to control later processing by feedback through parietal and temporal lobes. Such a flow pattern impresses on the brain a clear functional differentiation: prefrontal cortices act as goal systems to control more detailed lower level processing.

A set of coupled CNFT equations were developed in [21], and used as the basis of simulation of the Posner attention benefit effect, based on the above features. The simulation used differentiation of function by differences both in lateral connectivity and inhibition across modules as well as differences in the temporal flow of activity across modules. In particular we incorporated in [21] the early flow of activity to frontal lobes so as to act as an exogenous goal bias to the attention movement controller in parietal lobe, and thence feeding back activity to the sensory (and motor) cortices. This feedback is taken to be achieved by attention contrast gain applied in a quadratic sigma-pi manner to the input on the sensory cortical neurons. In terms of 3 modules, the goal module with neurons with activity g(**r**), the attention movement controller with activity v(**r**) and the input sensory module with activity u(**r**), the resulting control equations are [21]:

$$\tau \frac{du}{dt} = -u + w * I + w' * * I \times f(v) - h \tag{8}$$

$$\tau \frac{dv}{dt} = -v + w'' * f(g) \tag{9}$$
$$g = g_{des}$$

where g_{des} is the desired goal, and the dynamics in the goal system is being neglected. We can include both endogenous and exogenous attention goals by choosing g_{des} as the external input (in the exogenous case) or as a given externally determined activation to the goal system in prefrontal cortex. In (8) we use the notation $w * * I \times f(v)$ to denote the quadratic sigma-pi contrast gain amplification input, with

$$w * * I \times f(v) = \int w(r, r', r'') I(r') f(v(r'')) dr' dr''$$

as was used in [21] and references therein.

We have already noted that the attention control system (8), (9) can be used to simulate the Posner benefit and competitive processes. It has been extended to sensory motor attention control [3], [8]. More generally, the above control model has been extended so as to contain a monitor and a predictor of the future state, as in the CODAM model [8] and applied recently to simulate the attention blink in [23]. This was achieved by including a working memory or buffer module WM and a monitor MON. The new system of equations which update the set (8), (9) are now

$$\tau \frac{du}{dt} = -u + w * I + w' * * I \times f(v) - h \tag{10}$$

$$\tau \frac{dv}{dt} = -v + w'' * f(g) + w''' * F(MON) \tag{11}$$
$$-w'''' * f(WM)$$

$$g = g_{des} \tag{12}$$

$$MON = |WM - g| \tag{13}$$

$$\tau' \frac{dWM}{dt} = -WM + f(u) \tag{14}$$

where we have assumed that the input to the WM from the input processing layer is mainly excitatory. Moreover we have included a different time constant for the working memory buffer WM in (14) in order to allow for longer time constants (although we used in the AB simulation in [23] a set of reciprocally-coupled neurons as having greater flexibility, rather than manipulating the neuron time constants). We also use the extended Hebbian learning law

$$\delta w'(x, x', x'') = \epsilon f(u(x)).f(v(x'')).I(x')$$

where ϵ is a learning rate.

In equation (11) (and developed more fully in [23]) we included inhibitory feedback from the WM system to all nodes not coding for the input I in the attention movement In this way attention becomes a scarce resource: if a large attention load must be processed, say with many distracters, then the error can become large in the MON module, so will boost the size of the attention control signal, as in (11), and so be more effective against distracters.

We still have to face hard learning problems. The possibility of applying developmental knowledge to the learning process also needs to be considered. This can be achieved by including learning in an incremental fashion, so that lower level representations will be learnt first and stabilised, before further learning, under top-down control, is allowed. Furthermore the manner in which goal representations in prefrontal cortex could arise needs to be considered.

Emotion is minimally included by the addition of valence modules (amygdale and orbito-frontal cortex), following the emotion brain architecture already presented elsewhere [7], but now represented in the CNFT framework. We refer the interested reader to these developments.

For our attention control model to better approach the organising principles of the brain, we must replicate, for different modalities, the modules whose function is represented by the system of equations (10-14), comprising the goal, monitor, inverse model controller, buffer working memory and semantic/pre-processing modules. There are also regions of overlap of these modules for multi-modal attention processing. Learning must also be analysed for afferent as well as sigma-pi feedback weights; a developmental scheme has been developed elsewhere for an incremental approach to such a hard learning problem.

V. RESULTS OF THE PROGRAM

The basic results of the above program are of three sorts:

1) Understanding of the level of coupled bubble formation and dynamics, under simple feed-forward- & feedback coupling assumptions, with sizes and expected influences of bubbles on each other determined by relative parameter choices and fan-in values in the various modules. Some progress on this has already been made [13], and further structural results were presented in equations (3) to (10).
2) Learning of cortical representations, both of feed back and feed-forward form, can be obtained, supporting topographic spatial and localised object representations (using pre-specified fan-ins depending on the site of the CNFT module being considered).
3) Provision of a basis for addition of further complexity into the system, as well as applying other criteria, such as information maximisation, to constrain the approach. One of the unknowns in a general control problem is as to the quantity (if any) being optimised in the control system; for the brain it is expected to be a function of the total reward, although this cannot be evaluated solely by the net dopamine influx (since there are internal sources and non-dopaminergic rewards).

VI. RELATION TO BRAIN IMAGES

In [24] a derivation of a covariant structure equation models was given from an underlying (graded) neural network model of brain neural networks. An important component of this was the derivation of blood flow and BOLD signal levels $S(r,t)$ at position r and time t from underlying neural activity, summarised in the expression:

$$S(r,t) = \Sigma F(u(r',t'), r-r', t-t') \tag{15}$$

where the summation in (15) is over a suitably defined neighborhood round r, and a suitable time envelope round the time t; u denoted the activity of both excitatory and inhibitory neurons. A simple form for F is linear in u and exponentially falling off in t' around t.

A deduction of a structural equation was made in [24], of form

$$U(i) = \Sigma w(i,j)U(j) \tag{16}$$

in terms of activity variables $U(i)$ and their connection strengths $w(i,j)$, involving suitable pattern sets in different modules i, j, with the activity variables $U(i)$ obtained as linear projections of neural activity in a given module onto pattern templates. These templates are assumed to have been created by learning, and correspond to feature detectors (both at a low level and at object or action sequence level) running over a discrete set (as is observed in many parts of the brain, both for object representations as well as for atomic motor actions). The structural model (15), (16) thus involves neural activity as hidden variables, as expressed by (15). One take-home message from this is that structural models, if derived from underpinning neural activity, have a very different structure than those used directly on the brain imaging data: all neural activity is hidden (by (15)). This is made even stronger by the fusion of inhibitory and excitatory cell populations, so that the BOLD signal on the right hand side of (15) involves a summation over a component from each population.

VII. CONCLUSIONS

A general framework has been developed to analyse the global brain. It allows stable state analysis as well as extension to the temporal dynamics of a set of interacting CNFT modules. Learning presents also dynamical features that allow the analysis of pattern structure of the synaptic weights. Attention control was included by a sigma-pi contrast gain feedback mechanism. The nature of emotional modulation has yet to be properly inserted by use of reward learning, but this will be included in subsequent version of the multi-modular CNFT brain model.

Much work lies ahead, but general features have already been obtained that indicate the value of the approach.

Many open questions are still to be faced in the above framework.

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