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Quantum Decision-Maker Theory and Simulation

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ABSTRACT

A quantum device simulating the human decision making process is introduced. It consists of quantum recurrent nets generating stochastic processes which represent the motor dynamics, and of classical neural nets describing the evolution of probabilities of these processes which represent the mental dynamics. The autonomy of the decision making process is achieved by a feedback from the mental to motor dynamics which changes the stochastic matrix based upon the probability distribution. This feedback replaces unavailable external information by an internal knowledge-base stored in the mental model in the form of probability distributions. As a result, the coupled motor-mental dynamics is described by a nonlinear version of Markov chains which can decrease entropy without an external source of information. Applications to common sense based decisions as well as to evolutionary games are discussed. An example exhibiting self-organization is computed using quantum computer simulation. Force on force and mutual aircraft engagements using the quantum decision maker dynamics are considered.

1 Introduction

Quantum computers are under development at laboratories around the world. However, the number of powerful algorithms for use on future quantum computers has been limited because of the restrictions imposed by the quantum unitary operator. The unitary nondissipative process, central to quantum operations, does not readily allow the simulation of neural intelligence which can be classically simulated using, among other devices, dissipative attractors. One promising approach around this impasse develops the concept of Quantum Recurrent Nets (QRN) which has been proposed by Zak and Williams.[3] QRN takes advantage of the quantum measurement property which collapses the quantum probability wave and is subsequently reinitialized and thereby resets the recurrent process. Thus, the effective combined process is not limited to unitary processes only, and this ultimately allows the efficient simulation of human endeavors. This paper develops the Quantum Decision Maker theory which extends the QRN to include reflexive intelligence and simulates a Quantum Decision Maker.

The origin of the Quantum Decision Maker begins with consideration of that most mysterious human property, common sense. Common sense has been an obstacle for artificial intelligence even though it was well understood that human behavior, and in particular the human decision making process, is governed by feedback from the external world. Although part of the problem was successfully simulated by control of systems, when the external world does not provide sufficient information, the human being turns for "advice" to his experience, and that is associated with common sense. In this paper *we represent common sense by a feedback from the self image* (a *reflexive* concept adapted from psychology[5]), and based upon that, we will propose a physical model of common sense in connection with the decision making process.

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2 The Decision Making Process in Terms of Nonlinear Probabilities

In this section we formulate a nonlinear equation for the representation of the probability of choices. The decision making process can be modeled by the time evolution of a vector π whose components $\pi_i, (i = 1, 2...N)$ represent a probability distribution over N different choices. The evolution of this vector can be written in the form of a Markov chain,

$$\begin{gathered} \pi(t+\tau) = \pi(t) P \\ \pi_j(t+\tau) = \sum_{i=1}^{N} \pi_i(t) p_{ij},\ \sum_{i=1}^{N} \pi_i = 1,\ \sum_{j=1}^{N} p_{ij} = 1 \\ 0 \le \pi_i \le 1,\ 0 \le p_{ij} < 1 \end{gathered} \tag{1}$$

where p_{ij} is the transition matrix representing a decision making policy. If $P = const$, the process (1) approaches some final distribution π^{∞} regardless of the initial state π^0. In particular, in the case of doubly-stochastic transition matrix, i.e., when

$$\sum_{j=1}^{N} p_{ij} = 1,\ and\ \sum_{i=1}^{N} p_{ij} = 1 \tag{2}$$

all the final choices become equally probable,

$$\pi_i = \pi_j = \frac{1}{N} \tag{3}$$

i.e. the system approaches its thermodynamic limit which is characterized by the maximum entropy. When the external world is changing, such rigid behavior is unsatisfactory, and the matrix P has to be changed accordingly, i.e., $P = P(t)$. Obviously this change can be implemented only if the external information is available, and there are certain sets of rules for correct responses. *However, in real world situations, the number of rules grows exponentially with the dimensionality of external factors, and therefore, any man-made device fails to implement such rules in full.*

The main departure from this strategy can be observed in the human approach to decision making process. Indeed, *faced with an uncertainty, a human being uses a "common sense" approach based upon his previous experience and knowledge in the form of certain invariants or patterns of behavior* which are suitable for the whole class of similar situations. Such a reflexive ability follows from the fact that *a human possesses a self-image, and interacts with it.* This concept which is widely exploited in psychology has been known even to ancient philosophers, but so far its mathematical formalization has never been linked to the decision making model (1).

First we will start with an abstract mathematical question: can the system (1) change its evolution, and consequently, its limit distribution, without any external "forces"?

The formal answer is definitely positive. Indeed, if the transition matrix depends upon the current probability distribution

$$P = P(\pi) \tag{4}$$

then the evolution (1) becomes nonlinear, and it may have many different scenarios depending upon the initial state π^0. In the particular case (2), it can "overcome" the second law of thermodynamics decreasing its final entropy by using only the "internal" resources. The last conclusion illuminates the Schrödinger statement[2] that *"life is to create order in the disordered environment against the second law of thermodynamics."* Obviously this statement cannot be taken literally – as will be shown below. Eq. (1) subject to the condition (4) describes the system which is not isolated, and therefore, the result stated above does not violate the second law of thermodynamics. In order to discuss the physical meaning of the condition (4), let us turn to Eq. (1) and introduce the underlying stochastic process. The latter can be simulated by a quantum device represented by quantum recurrent nets (QRN),[3] and we will start with a brief description of that device.

2.1 Quantum Recurrent Nets

The simplest QRN is described by the following set of difference equations with constant time delay τ

$$a_1(t+\tau) = \sigma_i\left\{\sum u_{ij}(t)\, a_j(t)\right\}, i.e., \{a_0 a_{1...} a_n\} \rightarrow \{0,0...1...00\} \tag{5}$$

where a_j is the input to the network at time t, u_{ij} is a unitary operator defined by the corresponding Hamiltonian of the quantum system, and σ_1 is a measurement operator (in the computational basis) that has the effect of projecting the evolved state into one of the eigenvectors of σ_1. The curly brackets are intended to emphasize that σ_1 is to be taken as a measurement operation with the effect similar to those of a sigmoid function in classical neural networks. Obviously, the outputs $a_1(t+\tau)$ are random because of the probabilistic nature of quantum measurements. As shown by Zak and Williams,[3] these outputs form a Markovian stochastic process with the probabilities evolving according to the chain (1) and

$$p_{ij} = |u_{ji}|^2, \ \sum_{j=1}^{n} p_{ij} = 1, \sum_{i=1}^{n} p_{ij} = 1, \ p_{ij} \geq 0, \quad i,j = 1,2,...N \tag{6}$$

is the NxN doubly-stochastic matrix which is uniquely defined by the unitary matrix U. Each element of this matrix represents the probability that the i^{th} eigenvector as an input produces j^{th}eigenvector as an output:

$$\left\{00\ 0\ \underset{\uparrow}{1}\ 0\ \ 0\right\} \rightarrow \left\{00\ \ 0\ \underset{\uparrow}{1}\ 0\ \ 0\right\}. \tag{7}$$

In a special case when

$$p_{ij} > 0; \quad i,j = 1,2,...N$$

the Markov process is ergodic, i.e., the solution to Eq.(1) approaches an attractor (3) which is unique and it does not depend upon the initial value $\pi_0$at $t = 0$. Only this case will be considered in this paper. Thus, Eq. (5) describes the evolution of the vector

$$\{a_1...a_n\} =< \varphi, \quad \sum_{j=1}^{N} a_j^2 = 1 \tag{8}$$

representing a quantum state in a Hilbert space, and all the components (a_j, u_{ij}) are to be actually implemented. *This evolution is irreversible, nonlinear and nondeterministic because it includes measurements operations.* On the other hand, the vector

$$(\pi_1, \pi_2...\pi_n) = \pi, \quad \sum_{j=1}^{n} \pi_j = 1, \quad \pi_i > 0 \tag{9}$$

as well as the stochastic matrix p_{ij} exist only in an abstract euclidean space: they never appear explicitly in physical space. The evolution (1) is also irreversible, but unlike (5), it is linear and deterministic.

So far we have simulated the case $P = Const.$ In order to control P, let us assume that the result of the measurement, i.e., a unit vector $a_m(t) = \{00...010...0\}$ is combined with an arbitrary complex (interference) vector. If the reference state is

$$a' = \begin{pmatrix} a'_0 \\ a'_1 \\ \cdot \\ \cdot \\ \cdot \\ a'_N \end{pmatrix} \tag{10}$$

and σ is a measurement operator in the computational basis, then $|\psi(t+\tau)\rangle$, the recurrent state re-entering the circuit, must take one of the forms:

$$|\phi_0\rangle = \frac{1}{\sqrt{R_0}}\begin{pmatrix} 1+a_0' \\ a_1' \\ . \\ . \\ . \\ a_{N-1}' \end{pmatrix} = \frac{1}{\sqrt{R_0}}\begin{pmatrix} a_0^{(0)} \\ a_1^{(0)} \\ . \\ . \\ . \\ a_{N-1}^{(0)} \end{pmatrix} \tag{11}$$

$$|\phi_0\rangle = \frac{1}{\sqrt{R_0}}\begin{pmatrix} 1+a_0' \\ a_1' \\ . \\ . \\ . \\ a_{N-1}' \end{pmatrix} = \frac{1}{\sqrt{R_0}}\begin{pmatrix} a_0^{(1)} \\ a_1^{(1)} \\ . \\ . \\ . \\ a_{N-1}^{(0)} \end{pmatrix}$$

$$|\phi_0\rangle = \frac{1}{\sqrt{R_0}}\begin{pmatrix} 1+a_0' \\ a_1' \\ . \\ . \\ . \\ a_{N-1}' \end{pmatrix} = \frac{1}{\sqrt{R_0}}\begin{pmatrix} a_0^{(N-1)} \\ a_1^{(N-1)} \\ . \\ . \\ . \\ a_{N-1}^{(N-1)} \end{pmatrix}$$

with re-normalization factors:

$$R_0 = |1+a_0'|^2 + |a_1'|^2 + ... \tag{12}$$

$$R_1 = |a_0'|^2 + |1+a_1'|^2 + .. \tag{13}$$

$$R_{N-1} = |a_0'|^2 + |a_1'|^2 ... + |1+a_1'|^2 \tag{14}$$

It should be emphasized that the states (11) are first calculated and then prepared as new quantum inputs. The transition probability matrix, p_{ij} for this process is given by examining how each of the recurrent states, $|\phi_0\rangle ... |\phi_{N-1}\rangle$ evolve under the action of U:

$$p_{ij} = \begin{matrix} \left|\frac{b_0^{(0)}}{\sqrt{R_0}}\right|^2 & \left|\frac{b_1^{(0)}}{\sqrt{R_0}}\right|^2 & ... \\ \left|\frac{b_0^{(1)}}{\sqrt{R_1}}\right|^2 & \left|\frac{b_1^{(1)}}{\sqrt{R_1}}\right|^2 & ... \\ \left|\frac{b_0^{(N-1)}}{\sqrt{R_{N-1}}}\right|^2 & ... & \left|\frac{b_{N-1}^{(N-1)}}{\sqrt{R_{N-1}}}\right|^2 \end{matrix} \tag{15}$$

where

$$b_j^{(i)} = \sum_{r=0}^{N-1} u_{jr} a_r^{(i)} = u_{ji} + \sum_{r=0}^{N-1} u_{jr} a_r(0). \tag{16}$$

Thus, now the structure of the transition probability matrix p_{ij} can be controlled by the interference vector (10), and $P = P(t)$.

Let us now implement the internal feed back (4). For the purpose, assume that the components of the interference vector (10) are defined by the components π_i of the probability vector by setting:

$$a_i' = f_i(\pi_1, \pi_2, ...\pi_N) \tag{17}$$

and rewriting Eqs. (12)-(16) accordingly. Then

$$p_{ij} = p_{ij}(\pi_1 ... \pi_N) \tag{18}$$

However, the simplicity of this mathematical operation is illusive. Indeed, as pointed out above, the probability vector π is not simulated by the QRN explicitly: it has to be reconstructed by a statistical analysis of the ensemble of solutions to Eq. (5). In order to avoid that, one can simulate the evolution of the probability vector, i.e., Eq. (1) by a classical neural network which can be presented, for instance, in the form

$$\pi_1(t+\tau) = S\left[\sum_{j=1}^{N} w_{ik}\pi_k(t)\right] \tag{19}$$

where S is the sigmoid function, and $w_{jk} = const$ are the synaptic weights. Now Eqs. (5) and (19) are coupled via the feedbacks (6) and (17).

- From the mathematical point of view this system can be compared with the Langevin equation which is coupled with the corresponding Fokker Planck equation such that stochastic force is fully defined by the current probability distributions, while the diffusion coefficient is fully defined by the stochastic force.[4]
- From the physical viewpoint, Eqs. (5) and (19) represent two different physical systems (quantum and classical) which interact via the feed backs (4) and (6): the transition probability matrix P is defined by the unitary matrix U of the QRN according to Eq. (6), while the input interference vector to the QRN is defined by the feed back (17). Using the Feynman terminology,[1] Eq. (5) simulates probabilities, while Eq. (19) manipulates them.
- Finally, from the cognitive viewpoint, Eqs. (5) and (19) represent two different aspects of the same subject: the decision maker. Eq. (5) simulates his real-time actions i.e., his motor dynamics, while Eq. (19) describes evolution of self-image in terms of such invariants as expectation, variance, entropy (information), and that can be associated with the mental dynamics.

Thus, as a result of interaction with his own image and without any "external" enforcement, the decision maker can depart from the thermodynamical limit (3) of his performance "against the second law." Obviously, from the physical viewpoint, the enforcement in the form of the feedback (17) is external since the image (19) represents a different physical system. In other words, such a "free will" effort is not in a disagreement with the second law of thermodynamics.

Eqs.(5) and (19) illuminate *another remarkable property of human activity: the ability to predict the future.* Indeed, Eq. (19) depends only upon the prescribed unitary matrix U, but it does not depend upon the evolution of the vector a_i. Therefore, Eq. (19), *the predictive equation can be run faster than real time; as a result of that, future probability distributions as well as its invariants can be predicted and compared with the objective.* Based upon this comparison, the feedback (17) can be changed if needed.

Actually such *interaction with self-image simulates"common sense" which replaces an unavailable external source of information and allows one to make decisions based upon his previous experience.*

Formally the knowledge base is represented by the synaptic weight w_{jk} of Eq. (19), and its consists of two parts. The first part includes personal experience and habits (risk prone, risk aversion, etc.). The second part depends upon the objective formulated in terms of probability invariants (certain expectations with minimal variance, or maximum information, etc.). The dependence upon the objective may include real-time adjustment of synaptic weights w_{ij} in the form of learning (adapted from theory of neural networks). As soon as the synaptic weights are determined, the common sense simulator will follow the optimal strategy regardless of unexpected changes in the external world.

2.2 Exponential Increase in Information Capacity

It should be noticed that *the advantage of the quantum implementation is not only in simulation of true randomness, but also in exponential increase of information capacity.* Indeed, combining the direct product decomposability and entanglement, one can represent the unitary matrix in Eq. (5) as follows:

$$U = \left(U_l^{(1)} \otimes ...U_n^{(1)}\right) \bullet \left(U_l^{(2)} \otimes ...U_n^{(2)}\right) ... \left(U_l^{(m)} \otimes ...U_n^{(m)}\right) ... \tag{20}$$

Here the number of independent components is:

$$q = 4nm \tag{21}$$

while the dimensionality is

$$N = 2^n = 2^{\frac{q}{4m}} \tag{22}$$

In Eq. (22), N and q are associated with the Shannon and the algorithmic complexity, respectively; therefore, the exponential Shannon complexity is achieved by linear resources.

Further compression of Shannon information can be obtained by applying the ℓ -measurement architecture[3] when each step of the quantum evolution is repeated and measured ℓ times, and during a reset operation the results of all the measurements are combined with the previous state. As shown in,[3] such an architecture provides the double-exponential Shannon complexity:

$$N = 2^{\frac{q\ell}{4m}} \tag{23}$$

The advantage of the quantum compression (22) or (23) can be appreciated in view of the fact that the efficiency of an alternative device - the pseudorandom number generator - rapidly decreases with the growth of the dimensionality of random vectors.

Finally, one should notice that QRN provides the simplest physical simulation of the four constraints in Eq. (1). However, even if QRN is replaced by a random number generator, the quantum formalism should be preserved since it is the best mathematical tool generator for implementation of these constraints.

3 Spontaneous self-organization

We will start the analysis of the motor-mental dynamics, i.e., of Eqs. (5) and (19) with the effects of spontaneous self-organization with the system departs from the state of the thermodynamics limit and approaches a deterministic state without any external forces. For that purpose suppose that the selected unitary matrix in Eq. (5) is

$$U = \frac{1}{\sqrt{2}} \begin{pmatrix} 1 & -1 \\ 1 & 1 \end{pmatrix} \tag{24}$$

Then the corresponding transition probability matrix in Eq. (1), according to Eq. (6) will be doubly-stochastic:

$$P = \begin{pmatrix} \frac{1}{2} & \frac{1}{2} \\ \frac{1}{2} & \frac{1}{2} \end{pmatrix} \tag{25}$$

and the stochastic process (1) is already in its thermodynamics limit (3), i.e. $\pi_1 = \pi_2 = \frac{1}{2}$. Let us assume that the objective of the decision-maker is to approach the deterministic state.

$$\pi_1 = 1, \pi_2 = 0 \tag{26}$$

without help from outside. In order to do that, he should turn to his experience in the form of the feed back (17). If he chooses this feedback in the form:

$$a = (a_1, a_2),\ a_1 = -2\pi_i,\ a_2 = 1 \tag{27}$$

then, according to Eqs. (11-16), the new transition probability matrix p_{ij} transporting the interference vector will be:

$$\begin{array}{ll} p_{11} = \frac{\pi_l^2}{2\pi_i^2 - 2\pi_i + 1}, & p_{12} = \frac{(1-\pi_l)^2}{2\pi_i^2 - 2\pi_i + 1} \\ p_{21} = \frac{(1+\pi_l)^2}{2\pi_1^2 + 2} & p_{22} = \frac{(1-\pi_l)^2}{2\pi_1^2 + 2} \end{array} \tag{28}$$

The evolution of the probabilities π_1 is given by

$$\pi_i^{(n+1)} = \pi_1^{(n)} p_{1i} + \pi_2^{(n)} p_{2i}, \tag{29a}$$

and because of the property $\pi_2^{(n)} = \left(1 - \pi_1^{(n)}\right)$, π_1 can now be presented as:

$$\pi_i^{(n+1)} = \pi_1^{(n)} p_{1i} + \left(1 - \pi_1^{(n)}\right) p_{2i} \tag{29b}$$

in which $p_{11}$and p_{22} are substituted from Eq (28). It is easily verifiable that

$$\pi_1^{\infty} = 1, \pi_2^{\infty} = 0, \tag{30}$$

i.e., the objective is achieved due to the "internal" feedback (27).

4 Attraction to Common Sense Based Strategies.

Classical artificial intelligence as well as artificial neural networks are effective in a deterministic and repetitive world, but faced with the uncertainties and unpredictability, both of them fail. At the same time, many natural and social phenomena exhibit some degree of regularity only on a higher level of abstraction, i.e., in terms of some invariants. For instance, each particular realization of a stochastic process can be unpredictable in details, but the whole ensemble of these realizations i.e., "the big picture" preserves the probability invariants (expectation, moments, information, etc.), and therefore, predictable in terms of behavior "in general."

In this section we will map the hetero-associative memory problem performed by artificial neural nets onto the patterns which represent stochastic processes, namely: store a set of m stochastic processes given by vectors of their probability distributions

$$\pi^{(i)} = \pi_1^{(i)}, \pi_2^{(i)}, ..., \pi_n^{(i)}, i = 1, 2, ...m. \tag{31}$$

Do this in such a way that when presented with any of the process $\dot{\pi}^{(j)}$ of the set of M processes:

$$\overset{*}{\pi}{}^{(j)} = \overset{*}{\pi}{}_1^{(j)}, \overset{*}{\pi}{}_2^{(j)}, ..., \overset{*}{\pi}{}_n^{(j)}, j = 1, 2, ...M; \tag{32}$$

the coupled motor-mental dynamics (5), (19) converges to one of the stochastic processes (31). The performance

$$\overset{*}{\pi}{}^{(i)} \longrightarrow \overset{*}{\pi}{}^{(i)}, i = 1, 2, ...m; \tag{33}$$

represents correspondence between two classes of patterns, i.e., a hetero-associative memory on a height level of abstraction. Indeed, each process in (33) stores an infinite number of different patterns of behaviors which, however, are characterized by the same sequence of invariants (31) and (32), repetitively thereby representing a decision making strategy.

Hence, if the strategy of the decision-maker is characterized by a pattern $\dot{\pi}^{(j)}$from (32), starting from t=0, the external information becomes unavailable, he should change its strategy from the pattern $\dot{\pi}^{(j)}$to the corresponding pattern from (31), and that can be associated with a decision based upon common sense. It is implied that the attracting strategies π^i are sufficiently "safe", i.e., they minimize the risk taken by the decision-maker in case of an uncertain external world.

The first step in the implementation of the mapping (33) is to find the transition probability matrix P such that

$$\pi^{(i)} = \overset{*}{\pi}{}^{(i)} P \left(\overset{*}{\pi}{}^{(1)} \overset{*}{\pi}{}^{(2)} \ldots \overset{*}{\pi}{}^{(m)} \right). \tag{34}$$

This implies that the sought stochastic process is supposed to approach its limit state in one step, i.e.,

$$\overset{*}{\pi}{}^{(i)} (t+\tau) = \overset{*}{\pi}{}^{(i)} (t+2\tau) = \overset{*}{\pi}{}^{(i)} (\infty) = \pi^{(i)}. \tag{35}$$

Therefore, P must have the following form:

$$p = \begin{pmatrix} \pi_1 & \cdots & \pi_N \\ \pi_1 & \cdots & \pi_N \\ \vdots & & \vdots \\ \pi_1 & \cdots & \pi_N \end{pmatrix}, 0 < \pi_i < 1, \sum_{i=1}^{N} \pi_i = 1 \tag{36}$$

where the vector $\pi = (\pi_i ... \pi_N)$ belongs to the family of the vectors $\pi^{(i)}$ in Eq. (35). Indeed, then any arbitrary probability vector

$$X = (x_1, x_2, \ldots x_N) \tag{37}$$

is mapped onto the vector $\pi = (\pi_i ... \pi_N)$ in one step.

Let us assume that the vector $\pi = (\pi_i ... \pi_N)$ is representable as a direct product of n two-dimensional vectors,

$$(\pi_1, \pi_2 \ldots \pi_N), \tag{38}$$

$$n = \log_2 N. \tag{39}$$

Obviously this assumption imposes constraints upon the components of the vector π, and as a result, this vector can be defined only by $\log_2 N$ (out of N) independent parameters $\pi_j, i = 1, 2, ...n$. Now Eq. (36) reduces to

$$P = \begin{pmatrix} \pi_1 & 1-\pi_1 \\ \pi_1 & 1-\pi_1 \end{pmatrix} \otimes \ldots \otimes \begin{pmatrix} \pi_n & 1-\pi_n \\ \pi_n & 1-\pi_n \end{pmatrix} \tag{40}$$

where

$$p_{11}^{(k)} = p_{21}^{(k)} = \pi_k, \; p_{12}^{(k)} = p_{22}^{(k)} = 1 - \pi_k. \tag{41}$$

The next step in the implementation of the mapping (33) is to express the components of the matrix (40) via the components of the unitary operator U_{ij} (see Eq. (5)) and the interference vector (10). For that purpose, let us choose U_{ij} and α' as follows:

$$U = \begin{pmatrix} 1 & 0 & \cdots & 0 \\ 0 & 1 & \cdots & 0 \\ \cdots & \cdots & \cdots & \cdots \\ 0 & \cdots & 0 & 1 \end{pmatrix} = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} \otimes \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} \otimes \ldots \otimes \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} \tag{41}$$

$$a' = \left(a_1, a_{l(1)} + i\beta_{l(1)} \right) \otimes \ldots \otimes \left(a_n, a_{l(n)} + i\beta_{l(n)} \right). \tag{42}$$

Then, according to Eqs. (11-16),

$$p_{11}^{k}=\frac{|a_k+l|}{|a_k+l|^2+\left|a_{k(l)}^2+b_{k(l)}^2\right|}=\pi_k=p_{21}^{(k)}=\frac{|a_k|^2}{|a_k|^2+|a_{k(l)}+b_{k(l)}+l|}. \tag{43}$$

However, the components of the interference vector, $\alpha_k\alpha_{k(l)}$ and $\beta_{k(l)}$cannot be chosen independently since they should explore the equality (43) as well as the conditions:

$$l_m a_k=0, I_m a_{k(i)}=0, I_m b_{k(i)}=0. \tag{44}$$

Simple algebra leads to the following constraints imposed upon the interference vector:

$$a_1>-1, k=1,2,...n \tag{45}$$

$$a_{k(1)}=\frac{a_k^4}{2\left(a_k+1\right)^2}-\frac{\left(a_k^2+1\right)}{2} \tag{46}$$

$$\beta_{k(1)}=\sqrt{a_k^2-a_{k(1)}^2}. \tag{47}$$

Now the components π_k in Eq. (43) can be expressed via the only one component of the interference vector:

$$\pi_k=\frac{\left(a_k+1\right)^2}{\left(a_k+1\right)^2},\ 1-\pi_k=\frac{a_k^2}{\left(a_k+1\right)^2+a_k^2}=\widetilde{\pi}_k. \tag{48}$$

It is easily verifiable that $\widetilde{\pi}_k^{(j)}$ is the sigmoid function of a_k ,

$$\widetilde{\pi}_k=S\left(a_k\right) \text{since } \frac{\partial\widetilde{\pi}_k}{\partial a_k}\geq 0,\ \widetilde{\pi}_k\left(0\right)=0;\widetilde{\pi}_k\left(\infty\right)=\frac{1}{2} \tag{49}$$

and that property will be exploited later.

The final step is to implement the actual association between the patterns in the mapping (33), i.e., to find the appropriate dependence between the components π_k of the matrix (40) and the components of the pattern π^1. Since π_k are uniquely defined by a_k (see Eqs. (48)), we will start with representing a_k as linear combinations of the components of the initial patterns $\overset{*}{\pi}^j$ in the mapping (33) of each j^{th} association:

$$a_k^{(j)}=\sum_{i=1}^{N} w_{ik}\ \overset{*}{\pi}_i^{(j)},\ j=1,2,...m; k=1,2,...n \tag{50}$$

where w_{ik} are constant weights to be found, m is the number of association in Eq. (33), N and n are the dimensionalities of the input pattern $\overset{*}{\pi}^i$ and the output pattern π^j, respectively.

Eq. (50) can be written in the matrix form

$$A_{mn}=W_{nN}\Pi_{mN} \tag{51}$$

and therefore, the matrix W_{nN} of the weights can be explicitly expressed via the matrix A_{mn}, i.e.. via the components of he interference vector $a_k^{(j)}$:

$$W_{nN}=A_{mn}\Pi_{NN}^{-1} \text{ if } m=N, \det\Pi\neq 0 \tag{52}$$

$$W_{nN}=A_{mn}\left(\Pi^T\Pi\right)^{-1}\Pi \text{ if } m>N. \tag{53}$$

Eq. (52) presents the exact solution, while Eq. (53) gives a minimum norm approximation for the case when the number of association is large than the dimensionality of the input patterns $\overset{*}{\pi}^{(j)}$.

Since $a_k^{(j)}$ can be expressed via a probabilities $\pi_k^{(j)}$ of the transition probability matrix (38) by means of Eq. (48):

$$a_k^{(j)} = \frac{2\widetilde{\pi}_k^{(j)} \pm \sqrt{12\left(\widetilde{\pi}_k^{(j)}\right)^2 - 4\widetilde{\pi}_k^{(j)}}}{2\left(1 - 2\widetilde{\pi}_k^{(j)}\right)} \tag{54}$$

(one can choose either of two values), the problem is solved in a closed analytical form. Indeed, given the associations (33), one finds the corresponding $a_k^{(i)}$ by Eqs. (54), and then weights w_{ij} depend upon all the values of the input patterns $\overset{*}{\pi}_k^{(j)}$ (via the matrix Π) and the output patterns $\pi_k^{(j)}$ (via matrix A).

As soon as the weights w_{ij} are found, Eq. (19) can be represented in the following form:

$$\pi_i^{\infty} = S\left(\sum_{i=1}^{N} w_{ik}\pi_k^0\right), i = 1, 2, ...N \tag{55}$$

where

$$\pi_i^{\infty} = \pi_i\left(t \to \infty\right), \pi_k^0 = \pi\left(t = 0\right) \tag{56}$$

and the sigmoid function S is defined by Eq. (49). Eq. (55) has a form of a perception for hetero-associative memory. Exploiting this formal analogy, one can conclude that any input pattern π^o which is sufficiently close to a patter $\pi^{(i)}$ from the left of Eq. (33) will recall the output pattern which is close to the corresponding associative pattern $\overset{*}{\pi}^{(j)}$ from the right of Eq. (33). Moreover, due to the contracting property of the sigmoid function S in Eq. (55), the distance between the output patterns will be smaller than between the input ones. In particular, several different inputs can be mapped onto the same output, and that can be interpreted as a classification problem.

However, from the cognitive viewpoint, Eq. (55) is fundamentally different from the perception since it not only manipulates with the patterns of probabilities, but it also simulates them via the QRN. Indeed, Eqs. (50) defines the interference vector a' (see Eqs. (42)) which control the unitary evolution of QRN (see Eqs. (5) and Eq. (41)) in such a way that the generated stochastic process has exactly the same probability distribution as prescribed by the probability patterns π^{∞} manipulated by Eq. (55).

5 Theoretical Discussion

The model introduced above can be generalized in several ways. First we will consider the case when the decision-maker controls two different, but correlated processes by making choices for combinations of decisions with the joint probabilities π_{ij}. As mentioned in the introduction, the quantum implementation of stochastic processes, i.e., QRN, allows one to stay with the same evolutionary operator (41) with the only difference that now each step in QRN evolution should be run and measured twice, and then the results of these measurements, being combined with the interference vector (10) and normalized, are sent back as a new input. The sequences of the first and the second measurements correspond to the joint strategy for making decisions controlling two correlated processes. The physical origin of this correlation is quantum interference between the results of measurements after they are combined for a new input and subjected to the next step of unitary evolution.

Following the same methodology as those for a simple strategy, let us present a brief sketch of the double-

strategy model and start with the assumption similar to Eq. (38):

$$(\pi_{11},\pi_{12},...\pi_{NN}) \rightarrow \left(\pi_{11}^{(l)},\pi_{12}^{(l)},\pi_{21}^{(l)},\pi_{22}^{(l)}\right) \otimes \ldots \otimes \left(\pi_{11}^{(n)},\pi_{12}^{(n)},\pi_{21}^{(n)},\pi_{22}^{(n)}\right) \tag{57}$$

Then one can deal with each $2x2$ evolutionary operator in Eq. (41) separately. Any of these operators gives rise to the following transition probability matrix:

$$P = \begin{pmatrix} p_{11}^{11} & p_{11}^{12} & p_{11}^{21} & p_{11}^{22} \\ p_{12}^{11} & p_{12}^{12} & p_{12}^{21} & p_{12}^{22} \\ p_{21}^{11} & p_{21}^{12} & p_{21}^{21} & p_{21}^{22} \\ p_{22}^{11} & p_{22}^{12} & p_{22}^{21} & p_{22}^{22} \end{pmatrix} \tag{58}$$

where

$$\begin{gathered} p_{11}^{11} = \frac{|l+a_1|^4}{\left(|l+a_1|^2+|a_2|^2\right)^2}, p_{22}^{22} = \frac{|l+a_2|^4}{\left(|a_1|^2+|l+a_2|^2\right)} \\ p_{11}^{22} = \frac{|a_2|^4}{\left(|l+a_1|^2+|a_2|^2\right)^2}, p_{22}^{11} = \frac{|a_1|^4}{\left(|a_1|^2+|l+a_2|^2\right)^2} \\ p_{11}^{12} = \frac{|l+a_1|^2|a_2|^2}{\left(|l+a_1|^2\right)+|a_2|^2}, p_{11}^{21} = \frac{|a_1|^2|l+a_2|^2}{\left(|a_1|^2+|l+a_2|^2\right)^2} = p_{22}^{21} \\ p_{12}^{11} = p_{21}^{11} = \frac{\left|\frac{2}{\sqrt{2}}+a_1\right|^4}{\left(\left|\frac{1}{\sqrt{2}}+a_1\right|^2+\left|\frac{1}{\sqrt{2}}+a_2\right|^2\right)^2}, p_{21}^{22} = \frac{\left|\frac{1}{\sqrt{2}}+a_2\right|^4}{\left(\left|\frac{1}{\sqrt{2}}+a_1\right|^2+\left|\frac{1}{\sqrt{2}}+a_2\right|^2\right)} \\ p_{21}^{12} = p_{12}^{21} = p_{21}^{12} = p_{21}^{21} = \frac{\left|\frac{1}{\sqrt{2}}+a_1\right|^2\left|\frac{1}{\sqrt{2}}+a_2\right|^2}{\left(\left|\frac{1}{\sqrt{2}}+a_1\right|^2+\left|\frac{1}{\sqrt{2}}+a_2\right|^2\right)^2} \end{gathered} \tag{59}$$

In order to reduce the matrix (58) to the form (36), one has to provide the following equalities:

$$\begin{gathered} p_{11}^{11} = p_{12}^{11} = p_{21}^{11} = p_{22}^{11}, p_{21}^{12} = p_{12}^{12} = p_{21}^{12} = p_{22}^{21} \\ p_{11}^{21} = p_{12}^{21} = p_{21}^{21} = p_{22}^{21}, p_{11}^{22} = p_{12}^{22} = p_{21}^{22} = p_{22}^{22} \end{gathered} \tag{60}$$

Analysis of Eqs. (59) shows that only the four (out of twelve) equalities, namely

$$p_{11}^{11} = p_{22}^{11} = p_{12}^{11}, p_{22}^{22} = p_{11}^{22} = p_{12}^{22} \tag{61}$$

must be enforced since the rest of them will follow automatically. Hence, one has to choose the four components of the interference vector

$$a' = (a_1, a_2)\,; a_1 = a_{1(1)} + ib_{1(1)}; a_2 = a_{2(1)} + ib_{2(2)} \tag{62}$$

to enforce the four equalities in (61).

In principle, the problem is solvable, however, unlike the previous case (see Eqs. (45)-(47)) a closed from analytical solution is not available any more. A numerical solution can be based upon methods of gradient-descent. As a result, one arrives at the generalized model of motor-mental dynamics:

$$a_i\left(t+\tau\right) = \sigma_2\left\{\sum U_{ij}\left(t\right)a_j\left(t\right)\right\} \tag{63}$$

$$\pi_{ij}\left(t+\tau\right) = S\left[\sum w_{ijk\ell}\pi_{k\ell}\left(t\right)\right] \tag{64}$$

where σ_2 is a two-measurements operator.

Now the vector a_i simulates two correlated stochastic processes (corresponding to the first and the second measurements, respectively) whose joint probability π_{ij} is described by Eq. (64). Eqs.(63)and (64) are coupled in the same way in which Eqs. (5) and (19) are. Further generalization to the case of $\ell\,(\ell > 2)$ correlated strategies will require to replace $2x2$ components of unitary operators by $\ell x\ell$ components in the decomposition (41). As a result of that, the decomposition (57) should be changed accordingly.

The second line of generalization of the model considered in the previous section is associated with an objective function. Indeed, so far we did not discuss how the limit strategy π_i^∞ (see Eq. (55)) has been prescribed. In principle, such a prescription can be based upon the optimization of some objective function, for example: maximize entropy subject to a given expectation and variance, or minimize the expected cost function:

$$E = \sum_{j=1}^{N} c_j \pi_j^\infty \tag{65}$$

subject to the constraints:

$$0 < \pi_j^\infty < 1, \sum_{j=1}^{N} \pi_j^\infty = 1 \tag{66}$$

where c_1 are given weights representing the "external world." This minimization can be performed by linear programming, and as a result, the limit probability will be defined by the weights:

$$\pi_1^\infty = f_i\left(c_1, c_2, ...c_n\right). \tag{67}$$

However, in general, the weights c_i can represent the probability distribution of another stochastic process (on a much slower time scale) which belongs to a family of strategies converging to a global strategy in a way similar to the mapping (53). By continuing this process, one arrives at a hierarchy of stochastic attractors leading from local to global strategies on the higher an higher levels of abstraction. Such a hierarchy can be implemented by a set of master-slave equation of the type of (5) and (19).

In many practical cases, the objective function depends upon the outcome probabilities π_i^∞ and then Eqs. (65), (66) are coupled with Eqs. (5) and (19). This happens for instance, when the external world is represented by another decision-maker, and that situation can be interpreted as an evolutionary game.

5.1 Two Decision-Makers (Players)

Let us consider two decision-makers (players) and suppose that the first player's objective is to maximize the expected payoff after β number of moves:

$$E = \sum_{k=0}^{\beta} \sum_{i,j=1}^{N} \alpha_{ij} \pi_{ij}\left(t + k\tau\right) \tag{68}$$

$$\alpha_{ij} = const, \quad < \pi_{ij} < 1, \sum_{i,j}^{N} \pi_{i,j} = 1 \tag{69}$$

where π_{ij} are joint probabilities that the players will use the strategies i and j respectively. Then the objective of the second player is to minimize the maximum of E. If the objective (68), (69) is available to both players each of them can find the best strategy (for instance by applying the methods of dynamical programming) and implement it by simulations of Eqs. (63) and (64). However, it may happen that the players do not know exactly the objective. For instance, in the beginning they may ignore the correlation between their strategies assuming that

$$\pi_{ij} = \pi_i^I \pi_j^{II} \tag{70}$$

where π_i^I and π_i^{II} are the independent probabilities that each player will use a certain strategy. Then each player will have its own image of the objective:

$$E^I = \sum_{k=0}^{\beta} \sum_{i,j=1}^{N} \alpha_{ij}^I \pi_i^I\left(t + k\tau\right) \pi_j^{II}\left(t + k\tau\right) \tag{71}$$

$$E^{II} = \sum_{k=0}^{\beta} \sum_{i,j=1}^{N} \alpha_{ij}^{II} \pi_i^I (t + k\tau) \pi_j^{II} (t + k\tau) \tag{72}$$

and, based upon that, he will execute his strategy by running the corresponding version of Eqs. (63) and (64). After β numbers of moves, the feedback from the external world becomes available, and the players can evaluate their performance by comparing the differences:

$$\triangle^I = E^I - E, \ \triangle^{II} = E^{II} - E. \tag{73}$$

Based upon these differences, each of them can update the coefficients α_{ij}^I and α_{ij}^{II} in their objectives (71) and (72) respectively, and introduce correlations between π_i^I and π_j^{II} (such a re-evaluation of the objective can exploit the methodology of Bayes' procedures). Consequently, the player who has better images of the self and of the adversary has a better chance to win.

6 Numerical Quantum Computing Simulation of Nonlinear Probability Governing Spontaneous Self-Organization

In this section we simulate a quantum computer algorithm of spontaneous self-organization. Spontaneous self-organization is modeled by the evolution of nonlinear probability functions of Eq. (29). To perform this simulation both the quantum dynamics simulation algorithm and the nonlinear probability distribution algorithm are needed. The quantum based algorithm would, of course, normally be run on a quantum computer. Until such quantum computers are developed the algorithms are simulated using a classical computer.

6.1 Quantum Dynamics Algorithm

This section describes the stochastic implementation of the quantum dynamics part of the self-organization algorithm. The steps in the computation are as follows:

1. Since Quantum Recurrent Nets (QRN) need to relate to quantum measurements it is useful to define a matrix of measurements

$$\delta = \begin{pmatrix} 1 & 0 & ... & 0 \\ 0 & 1 & ... & 0 \\ ... & ... & ... & ... \\ 0 & ... & ... & 1 \end{pmatrix}, \tag{74}$$

with its elements $\delta_\ell^{(i)}$. For a 4 by 4 sample process that we compute below we have

$$\delta = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix}. \tag{75}$$

2. Add the matrix of measurements elements to the interference matrix elements $a_\ell^{\prime(i)}$ to obtain the recurrent state matrix elements $a_\ell^{(i)}$,

$$a_\ell^{(i)} = \delta_\ell^{(i)} + a_\ell^{\prime(i)}. \tag{76}$$

3. Compute the unnormalized recurrent state vector $b_j^{(i)}$ by multiplying the unitary matrix u with elements u_{jr} times the recurrent state matrix to obtain

$$b_j^{(i)} = \sum_{r=0}^{N-1} u_{jr} a_r^{(i)}. \tag{77}$$

4. Compute the renormalization vector elements

$$R_j = \sum_{i=0}^{N-1} a_j^{(i)} a_j^{(i)*}. \tag{78}$$

5. Compute the transition probability matrix elements by taking the complex conjugate and renormalizing,

$$p_{ij} = \frac{b_j^{(i)} b_j^{(i)*}}{R_i}. \tag{79}$$

6. Select a row from the matrix of measurements and create a result vector v from the product of measurement vector δ' and the transition probability P

$$v_i = \sum_j \delta'_j p_{ij}. \tag{80}$$

For example, $\delta' = [1000]$ is the first row vector of the measurement matrix for a 4 by 4 matrix, and $\delta' = [0100]$ is the second row. The term δ'_j would be the j^{th} element in the respective vectors.

7. Build bins where the first bin is from zero to the value of the first element v_1, and the second bin is from the value of $v_1$to v_2, and so forth to the value one. The bin intervals are proportional to the transition probabilities.

8. Use a random number generator which generates random numbers in the interval 0 to 1, and assign the first random number to the bin in which it falls.

9. Depending in which indexed bin the random number falls assign the corresponding measurement vector index for the next measurement cycle.

10. Keep track of the bin number in which the measurements fall and plot the frequency of occurrence of each bin number. The normalized frequency of occurrence is the probability.

EXAMPLE 1. *Quantum Probability Simulation*

As an example we compute the transition probabilities from a given unitary matrix, and also compute the probability distribution after taking 1000 steps of the Markov process. The transition probability does not change with time in this example. However, in a second example below we allow it to change with time by successive use and reinitialization of this algorithm, where the reinitialization depends on probability outcomes. The 4 by 4 unitary matrix

$$u = \begin{pmatrix} -.426364 - .40965i & .152799 + .449573i & .268873 - .52106i & .262525 - .110547i \\ .187355 + .25612i & .377974 - .0919836i & .624798 - .282139i & -.5189 + .0924264i \\ .478001 - .334466i & .230266 - .310334i & .0028144 - .0982155i & .164187 - .688263i \\ -.415635 + .190776i & -.263578 - .635931i & .419877 - .0166754i & .363206 - .0920733i \end{pmatrix} \tag{81}$$

where the interference vector is

$$a' = \begin{pmatrix} -.00741589 + .48916i \\ -.12314 - .667601i \\ .344441 - .149759i \\ .386876 - .095256i \end{pmatrix} \tag{82}$$

gives the transition probability

$$P = \begin{pmatrix} .579626 & .00222459 & .216761 & .201389 \\ .338022 & .0781686 & .156848 & .426962 \\ .785018 & .159218 & .0349651 & .0207996 \\ .471082 & .225005 & .28342 & .0204926 \end{pmatrix}. \tag{83}$$

The initial fixed point probability distribution over states is

$$\pi^0 = \begin{bmatrix} .579626 & .00222459 & .216761 & .201389 \end{bmatrix}. \tag{84}$$

The final fixed point probability distribution over states is found to be

$$\pi^{1000} = \begin{bmatrix} .5810 & .0730 & .1990 & .1470 \end{bmatrix} \tag{85}$$

after 1000 transitions. The computations were implemented on a pc computer, and the computation run time was short.

6.2 Self-Organization Quantum Dynamics Algorithm

The theory for the self-organization quantum dynamics is discussed above, and its implementation as an algorithm on a classical digital computer used the following steps:

1. Start with the transition probability matrix

$$P = \begin{pmatrix} \frac{1}{2} & \frac{1}{2} \\ \frac{1}{2} & \frac{1}{2} \end{pmatrix}. \tag{86}$$

2. Choose initial conditions

$$\pi_i = \frac{1}{2}. \tag{87}$$

3. Compute $\pi_j(k+1)$by making a set of m measurements using the current transition probability matrix using the process in the Quantum Dynamics Algorithm subsection. The number m should be large enough that the distribution of outcomes fairly represents the transition probability distribution in order to have good accuracy.

4. Compute a $p_{ij}(k+1)$ using $\pi_i(k+1)$ in

$$\begin{array}{ll} p_{11} = \frac{\pi_l^2}{2\pi_1^2 - 2\pi_i + 1}, & p_{12} = \frac{(1-\pi_l)^2}{2\pi_1^2 - 2\pi_i + 1} \\ p_{21} = \frac{(1+\pi_l)^2}{2\pi_1^2 + 2} & p_{22} = \frac{(1-\pi_l)^2}{2\pi_1^2 + 2} \end{array}. \tag{28}$$

This results in a nonlinear probability distribution process.

5. Repeat steps #3. and #4. for each time step advance.

EXAMPLE 2. *Self-Organization Nonlinear Probability Distribution Evolution*

The values of the probability distribution for the above initial conditions for six time steps were computed as

$$\begin{array}{ll} \pi_1(1) = 0.4980 & \pi_2(1) = .5020 \\ \pi_1(2) = 0.6340 & \pi_2(2) = .3660 \\ \pi_1(3) = 0.7760 & \pi_2(3) = .2240 \\ \pi_1(4) = .9310 & \pi_2(4) = .0690 \\ \pi_1(5) = .9950 & \pi_2(5) = .0050 \\ \pi_1(6) = 1.000 & \pi_2(6) = 0.000 \end{array} \tag{88}$$

Thus, as the theory predicts, the computational simulation shows that π_1 is attracted to 1 and π_2 attracted to 0 with increase in time.

7 Conclusions

The Quantum Recurrent Net (QRN) theory implementing reflexive intelligence has been developed and computational dynamics simulations demonstrating its practical implementation have been made. The extension to more complicated problems is underway. Already the problem has been formulated for the prey-predator and mutual aircraft pursuit problems and numerical algorithms are under development using the reflexive intelligence concepts and computational dynamics introduced above. QRN can be further developed for the modeling of more complicated force-on-force engagements and general social interactions resulting in far more realistic and useful predicitions.

Thus we have *introduced a new dynamical paradigm in the form of coupled motor and mental dynamics which is represented by a quantum generator of stochastic processes controlled by nonlinear Markov chains.* Based upon this paradigm, a quantum decision-maker has been proposed. New dynamical phenomena, namely spontaneous self-organization, attraction to common sense strategies, and a new approach to simulation of evolutionary games have been discussed. True quantum mechanical implementation would provide enormous storage, random number generation, and computational advantages.

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