WAVE PROBABILISTIC INFORMATION POWER

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Abstract: Paper summarizes the results in the area of information physics that is a new progressively developing field of study trying to introduce basics of information variables into physics. New parameters, like wave information flow, wave information/knowledge content or wave information impedance, are first defined and then represented by wave probabilistic functions. Next, relations between newly defined parameters are used to compute information power or to build wave information circuits covering feedbacks, etc.

Key words: *Wave probabilistic functions, wave probabilistic circuits, wave information power, quantum informatics*

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1. Introduction

The analysis presented in [8] brings the three main quantities:

- The *information quantity* of data – basic unit of information [bits]
- The *information flow* of data Φ – the speed of transmission of basic information units [bits per second]
- The *information/knowledge content* I – the measure of information received or knowledge's impact on the studied system [excess events' number per bit]

By using the above defined basic quantities, we can easily derive the other ones [1]. For example *information power* PI [2,4,5] can be defined as (we expect the time dependence of all used quantities):

$$PI\,(t) = \Phi\,(t) \cdot I\,(t) \tag{1}$$

Because the information flow of data Φ is expressed in [bits per second] and the information content I in [events per bit] we derive the unit of information power in ["excess" events per second].

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Information power PI can have direct impact on the *perception of time*. We can imagine that our normal time perception is determined by predefined events per second in our body. In case this number is higher, e.g. due to the received information, our time perception is more intensive and the inner time clock is faster. On the other hand, lower number of events per second in our body yields to perception that inner time is slowing down or that outer time is running quickly.

It is evident that the relation between the information flow of data Φ and information content I can have a lot of time dependent forms. In accordance with our understanding of electrical or mechanical analogies, we can define the *information impedance* Z expressing the acceptance of received information flow of data Φ by the studied system in following way:

$$I\left(t\right) = Z\left(t\right) \cdot \Phi\left(t\right). \tag{2}$$

Due to time dependence in (2) we can expect three basic types of impedances. The *information resistance* R that is time independent and yields into linear dependency between $I\left(t\right)$ and $\Phi\left(t\right)$:

$$I\left(t\right) = R \cdot \Phi\left(t\right). \tag{3}$$

The *information inductance* L yielding into the form:

$$I\left(t\right) = L \cdot \frac{d\Phi\left(t\right)}{dt}. \tag{4}$$

And the *information capacitance* C can be given in the form:

$$\Phi\left(t\right) = C \cdot \frac{dI\left(t\right)}{dt}. \tag{5}$$

The information resistance gives us information that the transmitted information flow $\Phi\left(t\right)$ has a direct impact on the studied system with defined attenuation – received number of bits per second is linearly dependent on the number of events per received bit on the studied system.

The information inductance says that the time change (increase/decrease) of information flow $\Phi\left(t\right)$ in small time interval (acceleration of transmitted bits) is linearly proportional to number of events per received bit on studied system. On the other hand, the constant information flow $\Phi\left(t\right)$ yields into a continually increasing number of events per bit on studied system.

The methodology defined above, which is able to describe the behavior of some observed information/knowledge content I, is not necessarily the same forever [6]. As a means of rejection of obsolete data and capturing changes in information/knowledge content I or in information flow Φ, the exponential or general forgetting [3] could be applied. Actually, data are not rejected but less relevant data (in a simplified view older data are considered less relevant) will be less weighted.

2. Active and Reactive Information Power

With respect to basic definition of information power PI given in (1) we introduce the phase parameter φ between information flow and content that defines the dependence between these two quantities. In other words, the parameter φ yields into introduction of *active information power*:

$$PI_A(t) = \Phi(t) \cdot I(t) \cdot \cos(\varphi) \tag{6}$$

or *reactive information power*, respectively:

$$PI_R(t) = \Phi(t) \cdot I(t) \cdot \sin(\varphi) \,. \tag{7}$$

In more general case, phase parameter can be dependent on time $\varphi(t)$.

Entering phase parameter in (1) brings new interpretation features of information power PI. First of all, both active and reactive power can reach positive and negative values. Positive active power can be interpreted as events which introduce more order in the system. On the other hand, in case of negative power these events bring more disorderliness into the system (information is withdrawn out of the system). Active information power for both above mentioned cases yields into real active events recognized on studied system that can be observed by external observer.

Reactive information power introduces new dimension into system theory that includes soft features, such as emotions, feelings, etc., which cannot be explicitly recognized by external observer. Inner events inside our system can bring some information which can stimulate creativity or productivity of active information power if suitably processed. In the same way, the reactive information power can reach positive and negative values where the positive reactive power represents something similar to approach to the state of euphoria. The negative reactive power describes depressed mood.

In analogy to our perception we can listen to music and all received information is processed in a positive reactive way (we do not make active events). But the music can stimulate our inner events, which can give us positive benefits. On the other hand, some information can evoke ill humor.

Maximum benefit can be obtained if we are able to process both active and reactive information (reasonable and emotional part of received information) and to achieve the maximum information power – total power given in (1).

It is easy to extend this approach and to define the *information power factor* as the ratio of the real information power to total information power.

3. Active and Reactive Information Power in Quantum Informatics

Wave probabilistic functions represent a deeper structure of information [12] and so all above introduced parameters should be redefined with respect to this approach.

3.1 Information quantities defined through wave probabilistic functions

The wave information quantity of data can be expressed through the wave probabilistic function $\psi(x, t)$ [11–14] depending on parameter x and time t. The system modeling and time evolution of wave probabilistic models were defined in detail in [3].

From the information physics point of view the quantity of information in bits can be measured e.g. by von Neumann entropy [7] as follows:

$$S\left(\rho\right) = -tr\left(\rho \cdot \log_2\left(\rho\right)\right), \tag{8}$$

where $tr(.)$ means trace operator and ρ density operator:

$$\rho\left(x,t\right) = \left|\psi\left(x,t\right)\right|^2. \tag{9}$$

It measures the amount of uncertainty contained within the density operator taking into account also wave probabilistic features like e.g. entanglement, bosonic or fermionic quantum objects, quantization, etc. The operations (8) and (9) transform wave probabilistic representation into a density operator and through it into a measure of information quantity.

With the help of such an approach we can define the time derivative of data wave information function which yields into the wave information flow of data "Φ_ψ" represented by the wave probabilistic function:

$$\psi_\phi\left(\Phi,t\right) = \left|\psi_\phi\left(\Phi,t\right)\right| \cdot e^{j\cdot\nu_\phi(\Phi,t)} \tag{10}$$

measured e.g. by von Neumann entropy in [bits per second]:

$$S\left(\rho_\phi\right) = -tr\left(\rho_\phi \cdot \log_2\left(\rho_\phi\right)\right) \tag{11}$$

$$\rho_\phi\left(t\right) = \left|\psi_\phi\left(\Phi,t\right)\right|^2. \tag{12}$$

The term wave information/knowledge content I_ψ enlarges information/knowledge content I into the wave probabilistic function:

$$\psi_I\left(I,t\right) = \left|\psi_I\left(I,t\right)\right| \cdot e^{j\cdot\nu_I(I,t)} \tag{13}$$

interpreted as the number of excess events per bit of received information.

The number of excess events in a studied system can also be measured by von Neumann entropy [bits of excess events of studied system per bit of received information]:

$$S\left(\rho_I\right) = -tr\left(\rho_I \cdot \log_2\left(\rho_I\right)\right) \tag{14}$$

$$\rho_I\left(I,t\right) = \left|\psi_I\left(I,t\right)\right|^2. \tag{15}$$

From the above analysis it is apparent that von Neumann entropy is just an information measure and plays the same role in the theory of wave probabilistic function as a classical Shannon entropy measure [7]. The wave probabilistic function carries all necessary information and/or application of any measurement results into loss of complete information. Due to this fact we propose to make all mathematical operations on the level of wave probabilistic functions (having incorporated all information inclusive phase factors), and at the end of this operation we can transform the final result into e.g. von Neumann entropy measure to obtain a physically understandable result [9, 14, 15].

3.2 Information power defined via wave probabilistic functions

Let us define two quantities in following way (for the sake of simplicity we suppose that all quantities are time independent):

$$\psi_\Phi = \alpha_{\Phi,1} \cdot |\Phi_1\rangle + \alpha_{\Phi,2} \cdot |\Phi_2\rangle + ... + \alpha_{\Phi,N} \cdot |\Phi_N\rangle \tag{16}$$

$$\psi_I = \alpha_{I,1} \cdot |I_1\rangle + \alpha_{I,2} \cdot |I_2\rangle + \cdots + \alpha_{I,N} \cdot |I_N\rangle\,, \tag{17}$$

where $\Phi_1, \ldots, \Phi_N$ and $I_1, \ldots, I_N$ are possible values of information flow and information content, respectively. Complex parameters $\alpha_{\Phi,1}, \ldots, \alpha_{\Phi,N}$ and $\alpha_{I,1}, \ldots, \alpha_{I,N}$ represent wave probabilities taking into account both probability of falling relevance flow/content value together with their mutual dependences [9].

The information power can be expressed through wave probabilistic functions as follows:

$$\begin{aligned}\psi_{PI} = \psi_\Phi \otimes \psi_I = \alpha_{\Phi,1} \cdot \alpha_{I,1} \cdot |\Phi_1, I_1\rangle + \cdots + \alpha_{\Phi,1} \cdot \alpha_{I,N} \cdot |\Phi_1, I_N\rangle + \cdots + \\ + \alpha_{\Phi,N} \cdot \alpha_{I,1} \cdot |\Phi_N, I_1\rangle + \cdots + \alpha_{\Phi,N} \cdot \alpha_{I,N} \cdot |\Phi_N, I_N\rangle\,,\end{aligned} \tag{18}$$

where symbol $\otimes$ means Kronecker multiplication [7], each i, j-th component $|\Phi_i, I_j\rangle$ represents particular value of information power that characterize the falling/measuring of information flow Φ_i and information content I_j.

Both values Φ_i and I_j could be either positive (the information is given into the system), or negative (information is withdrawn out of the system) or phase φ shifted with respect to (6) and (7). Generally, we can assign to values Φ_i and I_j separate phase factor $\varphi_{i,j}$. It means that each possible combination has different contribution to active and reactive information power.

It is evident that possible different combinations of information flows and contents $|\Phi_i, I_j\rangle$, $|\Phi_k, I_l\rangle$ can achieve the same (similar) information power:

$$\Phi_i \cdot I_j \approx \Phi_k \cdot I_l \approx K_r. \tag{19}$$

We can rewrite these two components of ψ_{PI} into one value as follows:

$$(\alpha_{\Phi,i} \cdot \alpha_{I,j} + \alpha_{\Phi,k} \cdot \alpha_{I,l}) \cdot |\Phi_i, I_j\rangle = \beta_r \cdot |K_r\rangle\,. \tag{20}$$

It could be seen that interferences of wave probabilities could emerge, and wave resonances among wave parameters are possible as well. Finally, an information power in wave probabilistic renormalized form can be expressed:

$$\psi_{PI} = \beta_1 \cdot |K_1\rangle + \beta_2 \cdot |K_2\rangle + \cdots + \beta_r \cdot |K_r\rangle + \ldots, \tag{21}$$

where the information power can be computed utilizing von Neumann entropy [“excess” events per second]:

$$S\left(\rho_{PI}\right) = -tr\left(\rho_{PI} \cdot \log_2\left(\rho_{PI}\right)\right) \tag{22}$$

in this case we have:

$$\rho_{PI} = |\psi_{PI}|^2\,. \tag{23}$$

The active and reactive information power can be computed by using the cosine and sine parts of information powers $|K_1\rangle, |K_2\rangle, ...$ in accordance with (6) and (7).

More generally, we can heuristically assign the criterion function $|K_{i,j}\rangle$ into each i,j-th component $|\Phi_i, I_j\rangle$. Afterwards, we can define the similar equation as (21) that respects our preference (criterion). This approach yields to the resonance principle between received/transmitted information flow and information/knowledge content with respect to our preferences. It enables to model deep perception and new soft systems categories for both input/output parameters of each circuit's element.

It is supposed that each element of information circuit has possible input/output information flow Φ_i and content I_j, as was given in [8]. With respect to this statement we can, therefore, define the input and output information power PI_{in}, PI_{out} assigned into this element. Due to resonance on input gate (21) which goes to increase of input power PI_{in} we can achieve an increase of output information flow.

3.3 Time-dependent wave probabilistic impedance

We can define the wave information impedance $\psi_Z(Z,t)$ expressing the acceptance of received information flow of data Φ by the studied system:

$$\psi_I(I,t) = \psi_Z(Z,t) \cdot \psi_\phi(\Phi,t). \tag{24}$$

In the same way, equations (2–5) can be rewritten for application of wave probabilistic functions:

The wave information resistance R_ψ yields into:

$$\psi_I(I,t) = R_\psi \cdot \psi_\phi(\Phi,t). \tag{25}$$

The wave information inductance L_ψ yielding into the form:

$$\psi_I(I,t) = L_\psi \cdot \frac{d\psi_\phi(\Phi,t)}{dt}. \tag{26}$$

And the wave information capacitance C_ψ can be given in the form:

$$\psi_\phi(\Phi,t) = C_\psi \cdot \frac{d\psi_I(I,t)}{dt}. \tag{27}$$

Due to the time dependence of all quantities $\psi_I(I,t), \psi_Z(Z,t), \psi_\phi(\Phi,t)$ we can use all the instruments known from the theory of electrical circuits – Laplace, Fourier or z-transform – and rewrite these quantities, for example, in $j\omega$-domain in the case of using Fourier transform $F[.]$ as follows:

$$\begin{aligned} \tilde{\psi}_I(I,j\omega) &= F[\psi_I(I,t)] \\ \tilde{\psi}_Z(Z,j\omega) &= F[\psi_Z(Z,t)] \\ \tilde{\psi}_\phi(\Phi,j\omega) &= F[\psi_\phi(\Phi,t)]. \end{aligned} \tag{28}$$

Then, the developed equations (27–29) could be expressed in $j\omega$-domain:

$$\begin{aligned}
\tilde{\psi}_I(I,j\omega) &= \tilde{\psi}_Z(Z,j\omega)\cdot\tilde{\psi}_\phi(\Phi,j\omega)\\
\tilde{\psi}_I(I,j\omega) &= R\cdot\tilde{\psi}_\phi(\Phi,j\omega)\\
\tilde{\psi}_I(I,j\omega) &= j\omega\cdot L\cdot\tilde{\psi}_\phi(\Phi,j\omega)\\
\tilde{\psi}_\phi(\Phi,j\omega) &= j\omega\cdot C\cdot\tilde{\psi}_I(I,j\omega)\,.
\end{aligned} \tag{29}$$

All the instruments/forms developed for electric circuits and applied in information physics in [4] could be applied also for wave information circuits.

4. Conclusion

Phase parameters and generally wave probabilistic functions bring into information physics a lot of new inspiration and open the quantitative way to the study of complex and, until now, just soft Systems categories, such as wisdom and ethics (as the highest classes of information).

The analogy can be seen in the application of transistors in electrical circuits that enables to design amplifiers, filters, etc. Such systems can leave the amplitude spectrum of wave probabilistic functions unchanged but they can significantly change the phase spectrum and so create links within these components – a probabilistic point of view will be unchanged but phase links can define creative links like in the human brain.

The wave information physics coming from the theory of wave probabilistic functions should be extended to others, until now unsolved problems. Like the principle of self-organization [10], e.g. We could also speak about the Kirchhoff Law, etc. An information system could be resistant to incorporating new pieces of information (information flow ϕ) because this new information turns into an extension of information content I and directly into more "excess" events per second on a studied system. The more "excess" events per second, the more energy spent due to the new piece of information. Self-organization should be caused by a regulating principle guaranteeing minimal energy spent in a studied system, or analogically by application of the Law of minimal information.

Our studied system can be described by wave probabilistic functions [9]. In the same way, system environment should be described with the help of wave probabilistic functions as well. It is reasonable that between a system and its environment a link represented by Kronecker multiplication also enables entanglement, etc. What happens if we make phase changes in our studied system? Will the phases of the wave probabilistic model of environment also be changed? We emphasize that modules of wave probabilistic models are unchanged. Should system environments react to phase changes in such a way that a global model (system plus environment) before and after phase changes remains the same (information conservation)? Could we measure phase changes of an environment to predict behavior of a studied system? There are still more questions than answers but we believe that wave information physics opens the door to new ideas and approaches.

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