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# Language Processing in Human Brain

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**Abstract**. Human brain is exceptionally complex and simple at the same time. Its extremely composite biological structure results itself in human everyday behavior that many people might consider rather simple than complex. In our research we will concentrate on the ways how a human brain can process English and other human natural languages because taken in general sense the ability to speak English or other human languages is only serious distinguishing feature that rises humans over the rest of the world making a human an intellectual being. On the purpose of our research we consider natural language as naturally formed symbolic system completely independent of these symbols' physical nature that is a little more general than a common natural language definition. The principles of natural language processing in human brain are most important for us if we want to build equally powerful artificial general intelligence. We start with the features of human brain neurons and neural networks, and step by step create a computer model of human brain networks that is able to process and generate a reasonable speech. We can't give a detailed explanation of human brain functionality in this short article. Moreover, it is not our goal, and such research is not complete yet. The main result of our research is revealing the principles how tiny single neurons working together can produce intellectual-like behaviour that exhibits itself in proper speech comprehension and generation in accordance with current context.

**Keywords**. Neuron, brain, neural network, intellect, language, AGI, human, mind.

## 1. Neurophysiologic Background

Intellect is a direct property of brain cerebral activity according to the Nobel Prize laureate R. Sperry [1]. From other side, human intellect is bound to natural languages that humans speak. Natural languages spoken by humans are in essence the only language system that provides comprehensive description of the world. It is obvious that the features of neural networks of human brain restrict the natural language basis. Moreover the basic operation set of natural language depends on universal methods of data transformation in real neural networks. We will show that taking the general features of human brain as base we can design a virtual device that has human intellectual abilities like English speech understanding and producing relevant speech answers. Everything can be built over English language then, even, for instance, such complicated abstract theories like theory of intellect [1] or constructive mathematics

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theory [2] because there is no other language or extra language means in the basics of these theories save English language.

Let us consider some general facts about human brain structure and neuron physiology. These facts would not be mentioned here if they didn't complete a base of our brain model. For the beginning, our model consists of a huge number of mutually linked independent information units without any central control like natural brain does. Those elementary information units of human brain are neurons. Neurons are connected to each other through their axons and dendrites that cover the large areas of human brain according to other Nobel Prize winner Santiago Ramon Cajal [3] who discovered this feature about a century ago. We are interested in two main neuron structures of a human brain: Neocortex and Cerebellum that both have a great similarity from the information point of view [4]. The number of neurons in these human brain structures is huge that is of great importance for us (our statistics will work perfect with such significant amount of data). Current estimates suggest that there may be on the order of $10^{10}$-$10^{12}$ neurons and of $10^{16}$ synapses per person. Each neuron has about 1000 connections on average [5] forming a kind of regular or, sometimes, granulated structure.

Natural neuron consists of cell body, number of dendrites, and one axon (generally we are not interested in internal neuron structure). Most of neurons consist of a cell body plus one axon and many dendrites. The axon is a protuberance that delivers neuron output signals to connections with dendrites of other neurons or with neuron cell bodies. Dendrites are other protuberances that provide plenty of surface area, facilitating connection with the axons of neurons. Dendrites often divide a great deal, forming extremely bushy dendrite trees. Axons divide to some extent but far less than dendrites. We don't reflect physical neuron structure in our model making the following generalization – our model elementary unit has many input signals and only one consolidated output signal that can be passed to many other model units.

There are several types of signals transmitting from one neuron to others as well as different types of data in human brain neurons [6, 7, 8]. We will abstract of the physical nature of mentioned processes taking in a view only their general external information features, in particular an impulse manner of signals.

Usually neuron does nothing active unless some function (we assign the letter $\Psi$ to it) of collective influence of all neuron inputs reaches a threshold level. Whenever that threshold level is reached, the neuron produces an output in the form of a short pulse that proceeds from the cell body, down the axon, and into the axon's branches. When this happens, the neuron is said to fire. From the external point of view the general manner of neuron firing seems to be stochastic except the case when neuron keeps firing during a certain period after it fired the first time. Sometimes neuron does not fire even if its threshold measured or estimated in the previous experiments is reached. Sometimes it fires spontaneously having no visible external factors to fire. This means that function $\Psi$ belong to a stochastic type. In addition, the neuron spontaneous activity (also of stochastic type) plays an important role in brain information processes, and it should be considered in our model through the features of function $\Psi$.

Axons influence dendrites over narrow gaps called synapses that are of a complex thin structure itself. Stimulation at some synapses encourages neurons to fire. Stimulation at others discourages or blocks neurons from firing. A complex stimulation provides answer that is hard to predict without exact information about states of neuron synapses and their dynamics. A lot of research was done to reveal the details of human brain synapse and neurons behavior [9, 10, 11, 12, 13, 14]. Nowadays the most of neuroscience researches confirm each other in general. There is mounting evidence that learning takes place in the vicinity of synapses and has something to do with the degree to which synapses translate the pulse traveling down one neuron's axon into dendrites of the next neuron or neurons. These results mean that function $\Psi$ is not constant but changes itself to support learning. However we will not create an exact model of synapse functionality. In our model we will use only general synapse features that were just mentioned above describing them through the function $\Psi$.

Brain neuron behavior was generalized in a simple information model [15, 16] which would help us in further analysis. Let $E^t_k$ be an event that some neuron has its synapse of number k activated at the time t. Then, supposing that zero time corresponds to the last time when function $\Psi$ has changed itself, a probability P of the neuron firing can be symbolically described as following

$$P = \Psi (E^t, E^0, U, M, N), N < M, \tag{1}$$

where $E^t$ and $E^0$ are vectors of synapse activity at time t and 0 respectfully, U is a probability that a neuron changes its reaction during one second due to the phenomenon of spontaneous activity, M is a total number of this neuron synapses, and N is a minimal number of active neuron synapses that are necessary to reach the neuron’s threshold. In other words, neuron can make decision to fire if only N of its M synapses are in the states they were at zero time.

The neuron synapse function (we will use the letter $\Psi$ for it) plays a key role in brain neuron functioning (e.g. in converging external synapse activity into neuron firing with a respect to previous history of neuron activity in a time-spatial form) [30]. It is obvious that function $\Psi$ is extremely complex and requires a powerful computer or even some advanced computer system to make an exact model even for a single neuron. Instead of using that approach we make only one natural assumption about $\Psi$:

**Principle 1.** If there is a configuration of dendrite activity (regardless of its type) and the neuron is active (e.g. firing) the function $\Psi$ modifies itself in the way that the neuron should fire on this particular or similar dendrite activity configuration in future.

This fundamental principle can be named as *principle of activity maintenance*.

This function $\Psi$ behavior leads to a recently confirmed fact that the same image repeatedly shown to human inspires activity of the same neurons in his brain. In its turn it leads to more complicated behavior when these activated neurons belong to one of specialized zones of the human brain, in particular, to the speech zone of the brain. In this case the human brain generates speech as a result of intellectual processing its input data. Principle 1 presumes that some physical process happens when brain memorizes information, and this process happens in the vicinity of neuron contacts (synapses mainly) because it is a place where activity signals of both contacting neurons meet. According to [11] it is probably the only place where such process occurs.

The next principle of simplifying $\Psi$ deals with a neuron spontaneous activity that was discovered and confirmed by many independent researches a long time ago. Spontaneous activity seems to be a mere noise producing by a neuron but really it is a fundamental feature. The second principle of brain functioning is:

**Principle 2.** There is a finite probability that any brain neuron fires independently of its current external configuration, history of firing, and the current states of its dendrite and axon inputs.

Further we will refer to this principle as a *principle of neuron spontaneous activity*.

In general our understanding of natural neuron functioning contains nothing more than:

- Neuron has two states: active when it fires and passive when it does nothing visible form the outside,
- Neuron can recognize the similarity of current synapse activity of other neurons connected to it and can react with firing on similar configurations of current synapse activity,
- Whenever active the neuron has a power to share its efforts with other neurons in order to activate or to suspend the activity of some other neurons including itself (actually knowing nothing about possible consequences of this activity),
- Neuron thoroughly follows principles 1 and 2.

Paying an undeniable respect to the researchers devoted their time to discover the details of natural neuron physiology nevertheless we have to admit that those details give us almost nothing about understanding the structure of the human intellect foundation.

Our aim is to prove that principles 1 and 2 lead to intellectual behavior if we speak about humans. In order to prove a memory phenomenon in neural networks of human brain we construct a mathematical model of natural neural network using principles 1 and 2. The deductions from this model form the basis for analysis of natural languages in a human manner.

This abstract model of natural language processing in relation to the respective human brain methods helps us to build more sophisticated models and check the different aspects of natural language processing in a human brain.

Finally, we build a complete abstract model - *General Sense Linker* (GSL) - of human brain methods for English language processing and synthesizing through generalization of some intermediate models that we will develop and also through direct implementation of model of the object that function $\Psi$ deals with. GSL learns English like a child who forms proper speech ability by himself using his/her parents' and teachers' lessons and examples. So, in order to do this, GSL should be provided with necessary conditions and examples for the automatic creation of output reactions on a contextual base.

After learning, GSL becomes almost fluent in English (certainly in the domain it was taught). This means that GSL's natural language responses on given natural language stimuli can be predicted in a current context by taking the similar human responses as a base. At the same time this GSL's behavior serves as a proof of mentioned above simple principles 1 and 2 of brain functioning because no extra fundamental features are used in GSL model save activity maintenance and spontaneous activity principles.

## 2. Natural Neuron network model

Let us consider a group of mutually connected neurons that we call *column*. All column neurons comply with the principles 1 and 2. We accentuate this fact by using italic font when mentioning the object *column*. In a general case the internal *column* neuron connections are supposed to be of some restricted chaos type that makes columns' information properties vary. Extern *column* connections consist of the set of column neurons' connections to the neurons that don't belong to the *column*. We divide extern column connections onto input and output parts (that parts can have connections in common sometimes). We consider the following virtual experiment in order to estimate a stability of column neuron reactions.

Suppose we have a neuron with number p (p-neuron) reacted with firing on some spatial configuration of activity coming from the external neurons to the dendrites of *column* neurons. In more precise, “spatial activity” means that we have a combination of external neuron signals constantly coming to our column neurons during some critical time period. This period is supposed be long enough to let column neurons to process these signals.

Formula (2) below shows probability $x^t_p$ of the event that a *column’s* p-neuron keeps its proper reaction on the concrete image $I_m$ exposed to the *column* exactly t seconds ago. By other words, p-neuron loses this reaction at the second with number t if the image $I_m$ has been exposed at a zero time point. The reason why this p-neuron changes its reaction can be explained through the *activity maintenance principle*: this neuron spontaneous activity occurred and this neuron merely amplifies its active dendrite ties when any other image was exposed to the *column* at this time point (like the results of research [28]).

Supposing that every *column* neuron needs an exact signal configuration on its dendrites to recognize the image (or by other words, dendrite activity configuration) we have the following equation for probabilities $x^t_p$ in the connection to other neural network parameters.

$$x^t_p=\left(\prod^{t-1}_{r=1}(1-x^r_p)\right)\cdot\{U+(1-U)[1-\prod_{i\in Q(p)}(1-x^{t-1}_i)]\}, \qquad (2)$$

where U is a probability that a *column* neuron changes its reaction during one second as it was defined in formula (1). Naturally, probabilities $x^0_p$ equal zero. The set Q(p) is designated to the variety of numbers of *column* neurons that provide p-neuron with relatively significant influence.

Let us take a look at figure 1 with a diagram of the numerical evaluation of the equation (2) under assumption that no neuron in a *column* has advantage over others, q equals 182 (we supposed it to be the estimated average size of human brain neural “column”) and U equals $10^{-7}$ (this probability means that 10,000 human brain neurons of Neocortex change their internal memory every second on average).

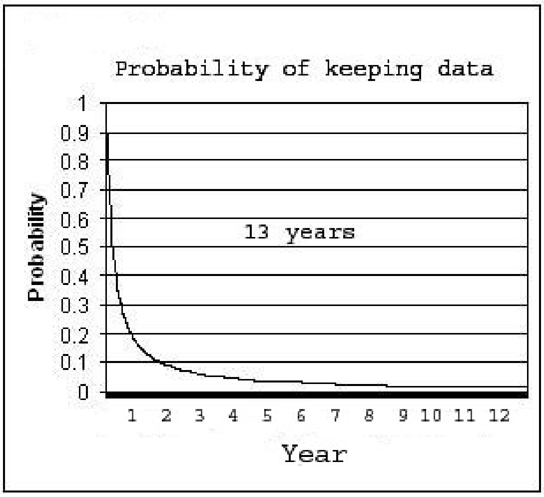

**Figure 1**. Probability of keeping the data in the Model

We need some additional model that can summarize the results of image remembering and recognition in our *column*s to create a consolidated reply like a human brain that generates consolidated answers. Fortunately we know that there is a brain Neocortex part with a plenty of giant pyramidal and motor neurons which generate signals resulting in speech. In this part there are outgoing peripheral brain nerves that control speech [11].

These pyramidal neurons collect and summarise signals of other neurons through their giant ramified dendrites covering the vast regions of a human brain. Many *column* neurons of some types with long horizontal-spread axons help them. Such pyramidal neurons regulate human speech facilities directly through generating signals to the throat and other muscles that are involved in a speech producing.

We introduce nothing new in pyramidal firing estimation. Formula that provides us with the means for estimating a probability of pyramidal neuron firing through vectors $E^t$ of its synapse activity (formula (1)) is

$$\Sigma_{k \in M} A(E^t_k, E^0_k) * W_k > \lambda,$$

where $A(\cdot, \cdot)$ is a function of two arguments that returns 1 if its arguments are equal, and 0 otherwise; $\lambda$ is some threshold, and $W_k$ are some weights associated to correspondent synapses (these weights are not constants, they vary according to the principles 1 and 2).

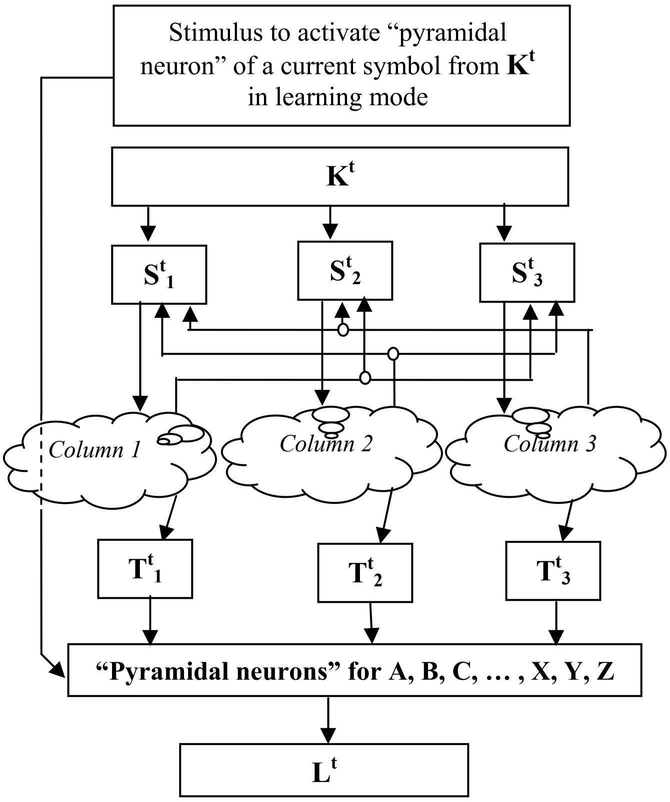

**Figure 2.** General Principle of Natural Language Phrase Processing in the Model

Unfortunately, a *human-like intellectual behavior* is a vague concept. Everybody understands it but can't express it formally at the same time. Broadly speaking, human is able to learn in any possible knowledge domain either quantum physics or car renting or almost any other field. From the external point of view this ability reveals itself in *generating relevant reactions on an appropriate input* in most cases. In more general, every generated English phrase should be consistent and should correspond to its predecessors. By other words, speech should be interconnected. We will believe that we have successfully proved that our abstract model has a human-like intellect if we will be able to show a similar behavior of our model.

We will consider many *column*s concurrently as a *column* system united by innumerous mutual ties of chaotic type (as it is shown formally by clouds on figure 2). This *column* system will be a core of our neuron network model. Statistical characteristics of the chaos are critically important as usual when any neuron network model is been built. We start with the simplest probability distributions (like normal) keeping in the mind to find the most effective ones through experiments with our computer model.

As far as English language is concern we will consider here only English letter and grammar symbol sequences $\{K^t\}$ as a brain model input no matter how they are delivered to brain either through vision, hearing or other relevant channel. Physically any peripheral neurons could deliver the consequences of signals that correspond $\{K^t\}$ through their ramified axons. Moreover we don't suppose to have functional level dependence here. Statistical one is enough for us. Our model accepts $\{K^t\}$ symbol by symbol having all information about the current symbol $C(K^t,t)$ processed before accepting the next symbol.

In its turn, $\{L^t\}$ stays for English letter or grammar symbol output of our model. We correlate it to the most active "pyramidal neuron" at the time (fig.2). Here the superscript index t corresponds to the time interval when actual symbol/letter was generated (or was entered in the case of $\{K^t\}$) in our neural *column* system.

The form of input doesn't matter for us because regardless of external symbol form the peripheral nerve system delivers information to brain as a combination of dendrite impulse activity. So what we can be sure in is that this dendrite activity correlates statistically with input symbols, and we need nothing more to know about input/output in our investigation.

We consider two modes of our model functioning: learning and speaking. At the first mode we have $\{K^t\}$ not empty, so our model has its current symbol anytime. At the second mode $\{K^t\}$ is empty, and we suppose that current symbol is $C(L^t,t-1)$ (model listens to its own "speech").

Let us number all neural *column*s using any appropriate method and let $S^t_i$ be an input of any particular *column* with number i at the time point t, and then let $T^t_i$ be the according *column* output that is a combination of *column* neuron axon activity. We also consider $T^t_i$ as some numeric measure of intensity of summarized *column* neuron activity in a relevant phrase context (the most frequent case is that there is not more than one active neuron in a *column* at any time point). In many cases just a numeric sum as measure is sufficient enough.

In the relation to our *column*s each variable $S^t_i$ means that there are some synapses on i-*column* neurons those synapses' weights are correlated somehow to letters and symbols those the model percepts and those are described by variable $K^t$. Formally $S^t_i$

includes some valuable subset of $K^t$ and feedbacks of previous neuron states of i-*column*.

All ties on the figure 2 provide not instant data transfer because natural axons and dendrites have different lengths and thickness, and sometimes because of different chemical environment in real neuron networks, feedback ties and because of the general inertia of a neuron functioning. These features are confirmed by many researches, for example, recent developments [25, 26, 27]. Action potentials travel at up to 10 m/s speed in unmyelinated axons and up to 120 m/s speed in myelinated axons [5]. Taking in a view these signal transferal delays, each $T^t_i$ is a complete mess of *columns*' neuron signals (in the form of impulses) if we consider them as an input sequence of some network neuron. One particularity of this "mess" is extremely important. *Column* will repeat this "mess" (configuration of outputs of its neurons) with the same statistical characteristics exactly if this *column* input is the same because *column*'s signal "mixing" algorithm statistically depends on dendrite-axon ties, length and thickness of dendrite and axons and some other constant factors that has been indirectly confirmed by many experiments mentioned in the first paragraph.

Finally, we constitute a simple but effective method to create a generalized output $L^t$ of "pyramidal neurons". We select a letter or a symbol of that "pyramidal neuron" which has currently a maximum activity level among all others as actual model output leaving the real algorithm for further investigation.

Nevertheless we use efferent and afferent signals in our model (the latter is a prototype for stimulus signal in fig. 2) in the learning mode. We suppose that efferent nerves have their corresponding afferent partners or the stimulation of a "pyramidal neuron" matching the current symbol can be done through efferent influence on receptor activity [31]. In our model this "afferent" direct or indirect stimulus provides additional activity to "pyramidal neuron" of a current letter when we teach our model.

## 3. COMPUTER-ADDED EXPERIMENT

It took about a year of intensive interactive communication with computer implementation of our abstract model (GSL) in order to achieve expected results. During this period the necessary statistics in the model were completed. The method that was used to teach the model plays a secondary role and therefore is listless here. The text material that was used to teach GSL consists of some child books, scientific articles, many dialog fragments of the type you can find in literature and Internet chats, on-line scientific, sport and politics news, and even thesaurus articles. A lot of direct interaction was done with GSL at the final stages of learning when reliable answers of GSL became common.

The experiment has proven that diversity of input texts and dialog topics leads to better results. Certainly the final model is not a comprehensive and complete artificial intelligence because of lack of knowledge and some data input/output stream simplifications (we had only one input stream and one output stream controlled by high level model monitor). Fortunately it was not our aim to create an artificial intelligence.

Bellow there are some samples of a dialogue with GSL model at the different stages of learning process (**G**: stays for free speech generation by GSL, **Q**: means a question, provided by teacher, and **A**: stays for GSL's answer to the question above).

GSL learning process passed through several stages. Each stage required its own settings and learning method specific modifications. Accordingly, the model behavior was improved stage by stage starting with exact answers to exact simple questions without taking the current context into account at primary stages, and to context speech generating at intermediate stages, and to free form answers to general questions in a complete conformity with context at final stages. Actually all these three stages are interconnected and differ only in a degree of context involving that in its turn is a result of amount of data that were accumulated in the model. Let us consider them consequently one by one.

Primary Stages (1,000,000 *columns*)
**Q**: *What's your name?*
**A**: *Alex*
**Q**: *How old are you?*
**A**: *I am a young man*
**Q**: *Who are you?*
**A**: *I'm a scientist*

At this stage the model was directly taught all these question-answer couples. It took several rehearsals for each question-answer couples before the model began to react properly.

Intermediate Stages (3,500,000 *columns*)
**G**: *He took no notice of this*
**G**: *He looked across of my companion who was also an elderly*
**G**: *I was away in a cab and down the platform, with what you had better give me much more clever than average man*
**G**: *I think that was to details of glance into the fire*

The model was not taught anyone of these sentences at any stage. No answers given by GSL were entered in the model in the exact form they were received. GSL generated them using its general knowledge collected throughout learning period in the context created by examiner especially for each sample. Also GSL computer model has read several books of famous English-speaking writers of last centuries. At the second intermediate stage it is common that all four sentences are of a correct syntax with some semantic disturbances that can be explained by a lack of knowledge in the model.

Final Stages (6,100,000 *columns*)
**Q**: *What is a sea floor?*
**A**: *A floor is generally a lower horizon*
**Q**: *What do you think about the mystery island colonists?*
**A**: *Poor wreckers! They were in a great danger*

Last answers look quite correct if we take in account that the context was the old trilogy of famous French child writer (in English translation) about underwater travel, oceans and isolated islands.

It should be especially mentioned that number of *columns* involved by teaching the model through dialogues and readings is not in a linear statistical dependence of processed data volume. The process of *column* number growth (our model has ability to create *columns* automatically when it is necessary) slows down with any portion of data that contains really new facts. For instance, the data volume processed at final stages is about ten times greater than similar amount at the intermediate stages. But at the same time the column amount in GSL model was only doubled (find these numbers above).

Table 3 contains a table with the learning stages against approximate numbers of neuron *columns* which activity is above average level, durations of the stages and intensity of new *column* neuron activation.

**Table.3.** Active *column* dynamics

| Stage | Amount of columns | Relative Duration | Average Intensity |
|---|---|---|---|
| *Primary* | 1,000,000 | 1 | 1.00 |
| *Intermediate* | 3,500,000 | 5 | 0.70 |
| *Final* | 6,100,000 | 14 | 0.43 |

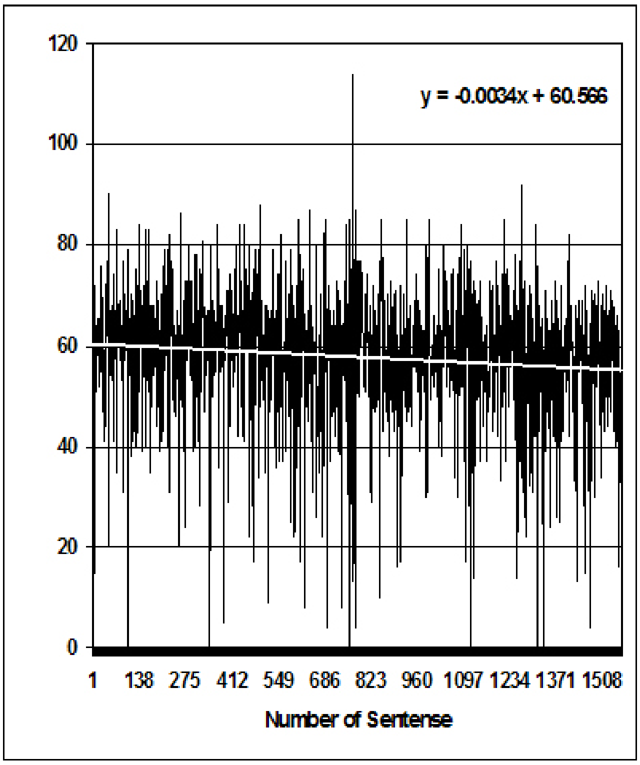

**Figure 3.** *Column* Involving Trend

Figure 3 illustrates the trend of the intensity of new *column* neuron activation against the number of processed sentences of some brief novel. The trend shows that intensity (y-axis) drops very slow but stable. Intensity is measured in average number of newly involved neurons (number of neurons per sentence length * 100) against the sentence amount.

When analyzing the results of experiments with *General Sense Linker* we keep in mind that *GSL* is NOT artificial intelligence (there is a long way to find out even what is a natural intelligence [29] saying nothing about artificial one). GSL is a model of natural brain neuron network that was created in order to explain how human brain works when processing the natural languages. Nevertheless GSL can be used as a language processor with not-symbolic internal knowledge representation. It is pretty effective to generate answers in a real time.

## 4. CONCLUSIONS

We discussed neither what a human intellect is nor how it could be built from not intellectual parts. It was enough for us that in spite of revealing itself in many different ways a human intellect always uses a simple ability of our minds to give natural answers to natural language questions in accordance with the questions' common sense and current context. We have shown this fundamental intellectual feature of our virtual device GSL that we created on the base of principles 1 and 2 and broad-known facts of human brain structure and physiology using them in a more or less constructive manner.

We have created GSL device that is capable to learn and speak English, and this device consists of a variety of independent comparably simple units which work without any synchronization and supervision like neurons in a natural brain. They are self-organizing and self-control units similar the brain neurons. Macro blocks of them that we called *columns* show the memory abilities, and we proved that *columns* can keep information as long as years at least.

GSL provides *columns* with input data and incorporates the results of *column* information processes into generalized output working similar the brain pyramidal neurons. So GSL device has a lot of features in common with human brain structures. For instance, knowledge is spread among the total set of neurons. So destroying some group of neurons doesn't result in destroying GSL's knowledge, it just becomes less solid.

Certainly it requires time to elaborate details and to persuade us that this device works having the same principles in its base as human brain has, and therefore explains how the latter works. But it can't stop us from using those principles and GSL device itself for many practical applications.

At the next stage of our research we will deal with visual input channel. Human vision is a complicated highly specialized apparatus that is tightly collected to the human general intelligence. So this research will use already created theory involving simple primary visual image recognition methods. We will show how video data that are not compact and grammar-structured like speech can be processed by our final GSL model having a similar result – generating the relevant answers to appropriate video images taken in a current context.

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