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EXPLORING THE USE OF LONG SHORT-TERM MEMORY (LSTM) IN FUNCTIONAL BASED BIOINSPIRED DESIGN

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Abstract: Bioinspired design is the rising discipline where biological cases are taken to inspire the designers to solve the engineering problems or challenges. The search of functional analogies using biological repository for analogies and inspirations acquisition based on engineering-to-biology thesaurus has proven to be an effective way. Whereas bias and inconsistency exist in the manually made thesaurus seriously hinders the exploration of biological cases. This research presents an Long Short-Term Memory (LSTM) based analogical reasoning methodology for bioinspired design, which focus on the realization of inter-disciplinary knowledge reasoning through extracting thesaurus from functional models automatically. Its effectiveness has been analyzed on an engineering-to-biology depository in terms of perplexity and functional models error rate. Furthermore, comparisons between the proposed method and other methods are given, and results show that considerable improvements are gained for analogical reasoning in functional based bioinspired design.

Keywords: *Bioinspired Design, Functional Model, LSTM, Concept generation*

1. Introduction

Billions of years of random mutation and natural selections tend to generate and optimize numerous remarkable biological skills in nature, which is a great treasure trove of design inspirations and analogies for product innovative design. However, traditional biological analogies or inspirations based design activities are limited by experience and reliance of designers, which lead to the less chance and randomicity of the generation of design solutions. Bioinspired design (BID) is viewed as powerful tools for modern product development innovation that seeks to mine biological knowledge to find design solutions through integrated use of multidisciplinary knowledge, such as design, biology, engineering and computer science.

Various methods in BID have been proposed, including unstructured natural language based methods and structured biological models based methods. Nagel et al. proposed a systematic functional analogy method, including a design repository for functional models reservation and an engineering-to-biology (E2B) thesaurus for inter disciplinary knowledge retrieval (Nagel, 2008). Sanaei et al. presented an ensemble model, combined by spatial representation of semantics, multi-level deep neural reasoning, graph matching based model and transformation-based model to achieve analogical reasoning (Sanaei, 2017). Glier et al. present an artificial intelligence method for leveraging the design knowledge within natural systems, which enables automatically identifying useful design analogies to improve keyword biological analogies search capability (Glier M W, 2014). The biomimicry institute developed Asknature.org to serve as a repository of biological knowledge and catalogs biological knowledge by function to bridge the gap between biology and other fields (Baumeister D, 2014). Srinivasan et al. found that the role of experience of designers on the use of analogies was not clearly ascertained and analogical transfer is observed only a few levels of abstraction while many levels remain unexplored (Srinivasan V, 2015). Hyunmin Cheong et al. found that the availability of associations from functional characteristics of biotic knowledge led to fixation, which influenced the designer's ability to obtain the relevant analogy (Hyunmin Cheong, 2012). Ma et al. presented a systematic biological modelling and analogical method, among which a functional blockings-function-behavior-structure model was proposed and realized inter disciplinary knowledge retrieval through consulting manually made engineering-to-biology thesaurus (Jin Ma, 2015). Such methods enable to aid in transforming knowledge from given biological analogies or inspirations to engineering solutions automatically. However, the inaccessibility of potential useful biological analogies and inspirations which are not given beforehand prevents designers from leveraging the full insight of the biological analogies or inspirations into the designed world.

As an expressive deep learning algorithm which is easy to train, LSTM has been proven to be a powerful method to solve classification, processing and time series prediction problems. LSTM deals with arbitrary-length sequences of input, which has the potential to extract mapping relationships among terms from different disciplinary and conducts analogical reasoning by taking functional basis based case representation model as training sequence (Nagel, 2008). Grounded on the above analysis, this paper presents an LSTM based bioinspired design method, which enables the extraction of interdisciplinary terms' mapping relationships from structured functional models automatically to acquire meaningful analogies and the realization of inter disciplinary analogical reasoning to generate design concepts.

2. Functional Modeling

Based on the thoughts of Suh's Axiomatic design theory (N. P. Suh, 2001), we have proposed an modular Function-behavior-structure (FBS) knowledge cell model (Jin Ma, 2015) for knowledge representation. As described in Fig. 1, FBS knowledge cell consists of function layer, behavior layer and structure layer. Working as functional blocks, sets of obtained FBS knowledge cells are saved in FBS knowledge cell repository hierarchically according to its decomposition process.

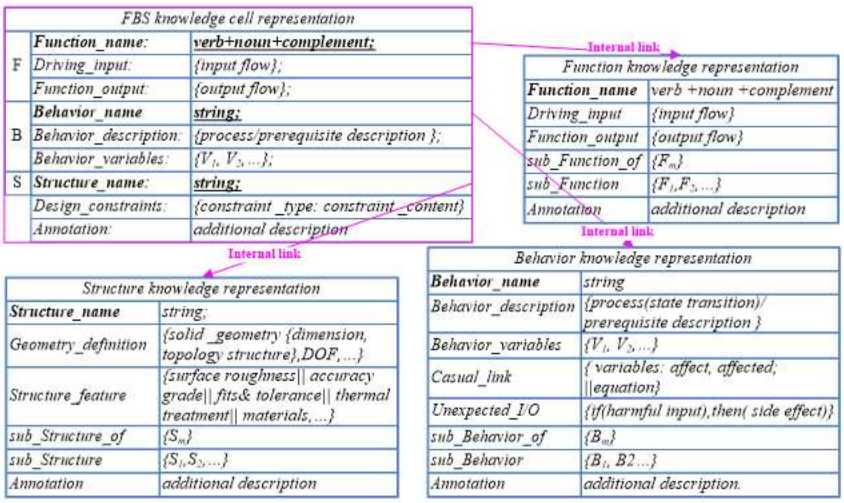

Figure 1. FBS knowledge cell representation

The proposed LSTM based bioinspired design starts right after abstracting source cases as a sequential of FBS knowledge cells, acquiring the corresponding FBS knowledge cells in target disciplinary, followed by assembling them head-to-tail in sequence according to *Driving_ input* and *Function_ output*.

Functional model of design cases is given in Fig.2, where $C_{fbs}^{e,i}$, $C_{fbs}^{b,j}$ expresses the engineering/ biological FBS knowledge cell model separately.

$$\boxed{C_{fbs}^{e,1}} \to \boxed{C_{fbs}^{e,2}} \to \cdots\cdots \to \boxed{C_{fbs}^{e,i}} \to \cdots\cdots \to \boxed{C_{fbs}^{e,m}}$$

Or

$$\boxed{C_{fbs}^{b,1}} \to \boxed{C_{fbs}^{b,2}} \to \cdots\cdots \to \boxed{C_{fbs}^{b,j}} \to \cdots\cdots \to \boxed{C_{fbs}^{b,n}}$$

Figure 2. Functional representation model of design cases

3. LSTM based Bioinspired Design Model

As the most widely used recurrent neural network (RNN), the LSTM can learn long-term dependencies and solve the long-term dependency problem in RNN. The LSTM achieved success in speech recognition, language modeling, natural language translation and picture description. LSTM is a feedback network that realizes the end-to-end analogical reasoning between biology and engineering through the encoding and decoding of sequential FBS knowledge models (Jin Ma, 2015). During the encoding stage, the encoder decouples and decomposes the specified source cases into functional models and serializes the functional models to a vector according to its Input flow and Output flow. And in the following decoding stage, the design concepts in target disciplinary are generated according to the obtained vector. Taking functional models' mapping from biology to engineering as an example. The potential relevance between the biological FBS knowledge cells and engineering FBS knowledge cells is fully excavated and the 'translation' of the input knowledge cells from the source disciplinary to the target disciplinary is achieved.

3.1. Construction of Training Sequence Set

The first problem of inter-disciplinary knowledge analogizing based on deep learning to solve is that how to build a training set which can meet the demand of the deep learning. Based on the existing inter-disciplinary knowledge cell base in our lab and more than 2500 bioinspired design cases built in the website called Asknature (http://www.asknature.org/) by Biomimicry institute (Baumeister D, 2014). These cases are analyzed and decomposed to form FBS knowledge cells, referring to the proposed knowledge modeling method. Function layer of given FBS knowledge cells are represented according to standard E2B functional verb list and input/ output flow list (Nagel, 2008).

During the construction process of training sequence set, the verbs and nouns embedded in the FBS knowledge cells from source disciplinary design cases are tagged first to form a vector and are encoded by 1-of-m coding where m is the number of input FBS knowledge cells. The FBS knowledge cells abstracted from corresponding design cases of target disciplinary are encoded in the same way by 1-of-n coding where n is the number of output FBS knowledge cells. Thus, the construction of the training sequence set is finished. FBS knowledge cells repository is gradually expanded and the reserved knowledge cells can be used as the training/test sequence set of LSTM based bioinspired design model.

3.2. LSTM based Bioinspired Design Process

The introduction of FBS knowledge cell, transforms design cases into a sequential of modular models according to its functional input and output flow, provides bioinspired design process with a consistent knowledge representation model to work as functional blocks. Thus, the inter-disciplinary knowledge analogy reasoning is transformed into the mapping relations learning and building between the inter-disciplinary FBS knowledge cells. The mapping relationships among terms derived from different disciplinary can be obtained by training neural network through interdisciplinary knowledge encoding and decoding process. The neural network based bioinspired design process is shown in Fig 3.

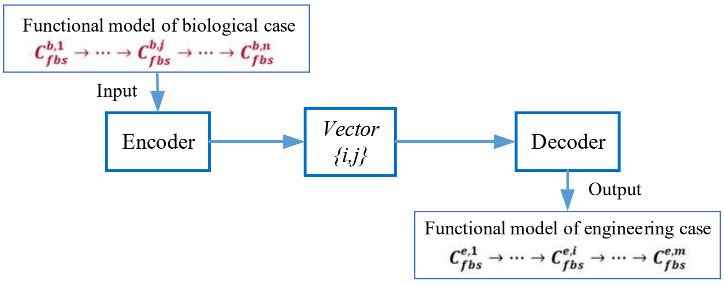

Figure 3. The neural network based bioinspired design process

LSTM neural network enables to predict the following knowledge cells on previous knowledge during interdisciplinary FBS knowledge cells analogical reasoning process. LSTM based bioinspired design model (Fig. 4) consists of a series of repetitive LSTM units that containing four interacting neural network layers. The input layer and the hidden layers encode input FBS knowledge cells into a fixed-length vector encoding, the output layer translates the encoded vector to FBS knowledge cells in target disciplinary. Expressions of the proposed LSTM based bioinspired design model are as following:

$$h_t = \emptyset(h_{t-1}, x_t) = f(W^{(hh)}h_{t-1} + W^{(hx)}x_t) \tag{1}$$

$$h_t = \emptyset(h_{t-1}) = f(W^{(hh)}h_{t-1}) \tag{2}$$

$$y_t = softmax(W^{(S)}h_t) \tag{3}$$

Where, $x_t \in R^d$ is the tagged verb and noun vector of the tth input FBS knowledge cell. $h_t = \sigma\left(W^{(hh)}h_{t-1} + W^{(hx)}x_t\right)$ is the transfer matrix, which is used to calculate hidden layer output during iteration process. $W^{(hx)} \in R^{D_h \times d}$ is the weight matrix that is calculated by the output in the previous iteration. $h_{t-1} \in R^{D_h}$ is the calculated matrix based on the $t-1$th iteration. When $t = 0$, it represents the initialization hidden layer output vector. $\sigma()$ expresses the sigmoid classification function, $y_t \in R^{|V|}$ states the output probability distribution of the tth iteration. $|V|$ of $W^{(S)} \in R^{|V| \times D_h}$ states all FBS knowledge cells in target disciplinary.

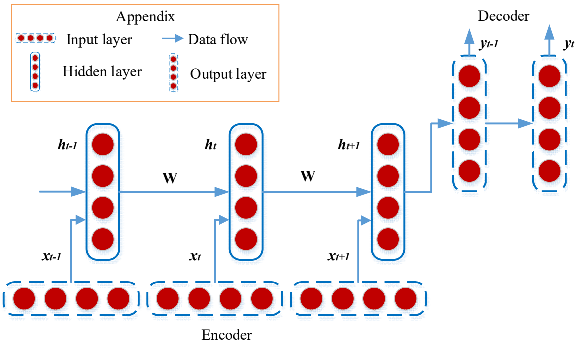

Figure 4. LSTM based bioinspired design process model

LSTM unit consists of input gate, memory gate, output gate and a cell unit. It's model and mathematical expressions are shown in Fig. 5. c_t is state cell, the line connects input gate (x_t, h_{t-1}) and output gate h_t is the state value of cell. f_t, i_t, o_t represented by the sigmoid activation function are oblivious gates. The input gate and the cell unit status are converted using $tanh$ function.

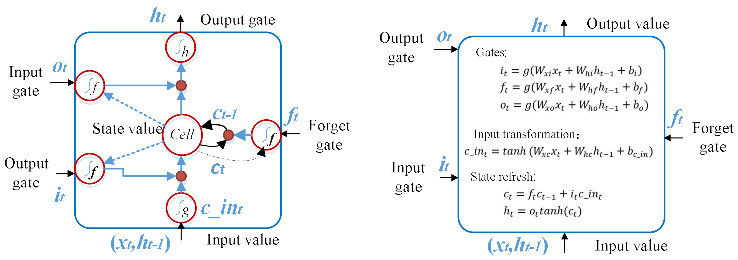

Figure 5. The repeated modules and mathematical expressions in LSTM units

LSTM based bioinspired design focus on acquiring the interdisciplinary mapping relationships implicitly embedded in the encoded FBS knowledge cells between biological domain and engineering domain and the learned mapping relationships of terms among different disciplinary are retained in the terms of neural network parameters. The trained neural network enables to transform the source cases into functional model formed by FBS knowledge cells of target disciplinary. The LSTM units based deep learning architecture for bioinspired design is given Fig. 6. $\{C_{fbs}^{e,i}\}$, $\{C_{fbs}^{b,j}\}$ represents the engineering/ biological FBS knowledge cells, separately, and each box states a LSTM unit.

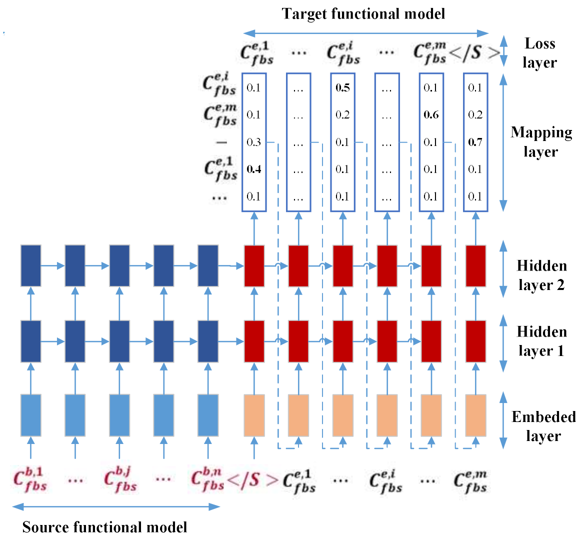

Figure 6. The LSTM units based deep learning architecture for BID

According to Fig. 6, the LSTM based bioinspired design process can be described as following:

Step 1. The training step of LSTM neural network to obtain network parameters;

At the input layer, the verbs and nouns embedded in the abstracted FBS knowledge cells from source disciplinary design cases are tagged first to form a vector and encoded later. At the output layer, the FBS knowledge cells abstracted from corresponding design cases of target disciplinary are encoded in the same way. Thus, the construction of the training sequence set is finished. The training sequence set are specified into LSTM neural network for training. The mapping relationships among interdisciplinary terms are acquired and retained in the terms of network parameters.

Once the expected output of target disciplinary is different from the actual result, the error value for each neuron is calculated inversely. The error is propagated along the knowledge cell chain backwards. Along with this process, the structure parameters of each layer in the network will be updated based on the error mainly.

Step 2. The analogical reasoning step of the trained LSTM neural network to acquire interdisciplinary FBS knowledge cells;

During the analogical reasoning step, the functional model of given design requirements are abstracted first and represented as a sequential of FBS knowledge cells $C_{fbs}^{b,1} \rightarrow \cdots \rightarrow C_{fbs}^{b,j} \rightarrow \cdots \rightarrow C_{fbs}^{b,n}$. Followed by specifying the encoded FBS knowledge cells into the trained LSTM neural network. When arriving at the </ S> which states the end of specified functional model, A sequential of FBS knowledge cells $C_{fbs}^{e,1} \rightarrow \cdots \rightarrow C_{fbs}^{e,i} \rightarrow \cdots \rightarrow C_{fbs}^{e,m}$ in target disciplinary can be acquired through neural network decoding process. During the analogical reasoning process, the analogical reasoning result of the former FBS knowledge cell works as the input of the latter FBS knowledge cell. The generation of the next interdisciplinary FBS knowledge cell in target disciplinary based on the hidden layer state and its current input. The analogical reasoning process is terminated when the </ S> symbol is generated. The translated FBS knowledge cell based functional model, consists of a sequential of FBS knowledge cells of the

target disciplinary, is generated. This step can also be described as: decoding the required function in the source disciplinary and re-encoding this function in the target disciplinary.
According to the total probability thought, the judgement of suitable generated functional models is transformed into the probability calculation. The functional model satisfies that the probability function: $P(C_{fbs}^{e,1}, \dots, C_{fbs}^{e,i}, \dots, C_{fbs}^{e,m})$ could reach the setting threshold is viewed as the proper ones.
Importing the maximum likelihood estimation (MLE) method, the problem of finding the parameter values that maximize the likelihood loss function is converted into the problem of solving the parameter values to obtain a minimization value, MLE for design concepts evaluation is defined as:

$$Loss\left(C_{fbs}^{e,1}, \dots, C_{fbs}^{e,i}, \dots, C_{fbs}^{e,m}|\theta\right) = -log\left(C_{fbs}^{e,1}, \dots, C_{fbs}^{e,i}, \dots, C_{fbs}^{e,m}|\theta\right) \tag{4}$$

Step 3. The design concepts generation step to reuse the knowledge cells as functional blocks to generate design solutions.
The output sequential functional model is represented as a sequential of end-to-end connected FBS knowledge cells. In this step, outputs of the former FBS knowledge cell are in conformance with inputs of the latter FBS knowledge cell to guarantee the generated design solution workable. Finally, structure knowledge invokes to generate design concepts. The model can conduct both biology-to-engineering (B2E) analogical reasoning and engineering-to-biology (E2B) analogical reasoning.
The above steps are repeated until a satisfied design concept is developed.

4. Case Study and Performance Evaluation

4.1. Case study

The case study utilized here has been used to evaluate the method in the design of a visual prostheses intended to restore vision. The bioinspired design process starts from abstracting functional model represented as FBS knowledge cells from specified design requirements, ends with design solutions generation through biological-to-engineering disciplinary analogical reasoning.
The nominal reflex arc of the visual prostheses is described in Fig. 7. According to functional modeling method in Section 2, the decomposed FBS knowledge cells based functional model of human visual mechanism to 'Form vision' has been built in Fig. 7.
Based on the LSTM neural network and FBS knowledge cell repository, the proposed bioinspired design method allows the design process to conduct knowledge finding without E2B thesaurus sorted. Even if designers don't have interdisciplinary education background, potential useful biological design analogies can be acquired. Totally 1765 existing FBS knowledge cells collected have been used to train the proposed LSTM based bioinspired design model. The trained LSTM neural network for bioinspired design would be used to conduct analogical reasoning tasks. Assume the function we want to translate is 'acquire visual information', the knowledge cells own the phrases 'sense light, detect light, perceive light, focus light', which beyond the beforehand sorted E2B thesaurus, are pushed to designers. After the analogical reasoning process, the acquired design analogies are given in Fig.8
Then abstracting the 'sense light, detect light, perceive light, focus light' mechanism of acquired design analogies into functional model and realize the B2E analogical process.

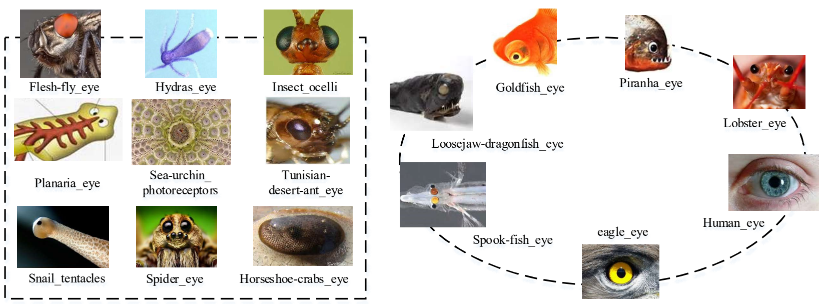

Figure 8. Interdisciplinary design analogies using LSTM based BID model

4.2. Performance evaluation for the proposed method

In this section, a series of experiments are designed to validate the effectiveness and to evaluate the performance of the proposed method. The effectiveness of proposed method is verified by comparing with other analogical reasoning methods, the perplexity, functional models error rate, average number of cross disciplinary corresponding knowledge cells are all trade-off factors. The perplexity (*PP*) and functional models and error rate (*NR*) are defined as following:

$$PP=\frac{1}{m}\sum_{i=1}^{m}((\prod_{j=1}^{N}\frac{1}{P\left(C_{fbs}^{j}\middle|C_{fbs}^{j-1}\right)})^{\frac{1}{N}}) \tag{5}$$

$$NR=\frac{1}{m}\sum_{i=1}^{m}(\frac{N_{error}}{N}) \tag{6}$$

Where, $C_{fbs}^{1} \ldots C_{fbs}^{N}$ is a sequential of FBS knowledge cells in biological domain, *N* is the number of the sequential of FBS knowledge cells , N_{error} is the number of the error FBS knowledge cells in engineering domain, and *m* is the number of the sequences. The design experiments are classified into three levels: low-level design, medium-level design and high-level design, according to its design complexity. Designers are grouped into experienced designers with rich interdisciplinary design experience and inexperienced designers with little interdisciplinary design experience. They are selected as subjects for objective evaluation. The comparison of proposed method and other existing methods is listed in Table 1. Based on comparison results in Table 1, our proposed method outperforms with results of Nagel's E2B thesaurus & morphological matrix based method and Chou et al.'s & morphological matrix based method. Experiments show improvements of about 40.5% and 54.3% relative in perplexity over E2B thesaurus & morphological matrix based method and Chou et al.'s & morphological matrix based method. In addition, we gain considerable improvements in robustness of design concepts generation: The higher the design level is, the more obvious the advantage of the proposed method. Moreover, when trained end-to-end with suitable regularization, we find that LSTM neural network achieves a functional models error of 8.9%, 16.7% and 32.1%, which to our knowledge is the best recorded score. The capability of the proposed method has been greatly improved over existing methods.

Table 1. Comparison of proposed method and other existing methods

Method	Perplexity (%)		Functional models error rate (%)		Generated design concepts (ratio)	
	Experienced	Inexperienced	Experienced	Inexperienced	Experienced	Inexperienced
Our proposed method:						
Low.	100	94.7	8.9	9.6	6.1	5.4
Medium.	98.4	89.6	16.7	23.8	5.6	4.8
High.	89.8	85.7	32.1	35.3	5.3	4.1
E2B thesaurus & Morphological Matrix:						
Low.	100	86.0	0	17.6	1.6	0.9
Medium.	95.7	72.9	13.2	35.2	1	0.6
High.	63.9	37.9	36.1	48.8	0.8	0.5
Chou et al. & Morphological Matrix:						
Low.	100	84.6	0	33.2	3.2	2.9
Medium.	93.5	76.1	21.5	44.1	2.6	1.9
High.	58.2	33.3	45.8	56	1.1	1.5

5. Conclusion and Discussion

In this article, we introduced a new LSTM based bioinspired design method for interdisciplinary design concepts generation. In order to build this model, an FBS knowledge cell model, works as functional blockings, is introduced. The LSTM units based neural network is incorporated into analogical reasoning process to realize automatic design process. Design-related knowledge used in the model includes both engineering and biological FBS knowledge cells. Finally, experiments were conducted to demonstrate that our proposed method was effective and outperforms than traditional analogical reasoning methods in bioinspired design.

Limited by the scale of the FBS knowledge cell library, the performance of the proposed method leaves much space to improve. For future work, more interdisciplinary FBS knowledge cells derived from bioinspired design cases will be collected to expand our training sequence set and FBS knowledge cell library and the automatically FBS knowledge cells extracting method will be researched.

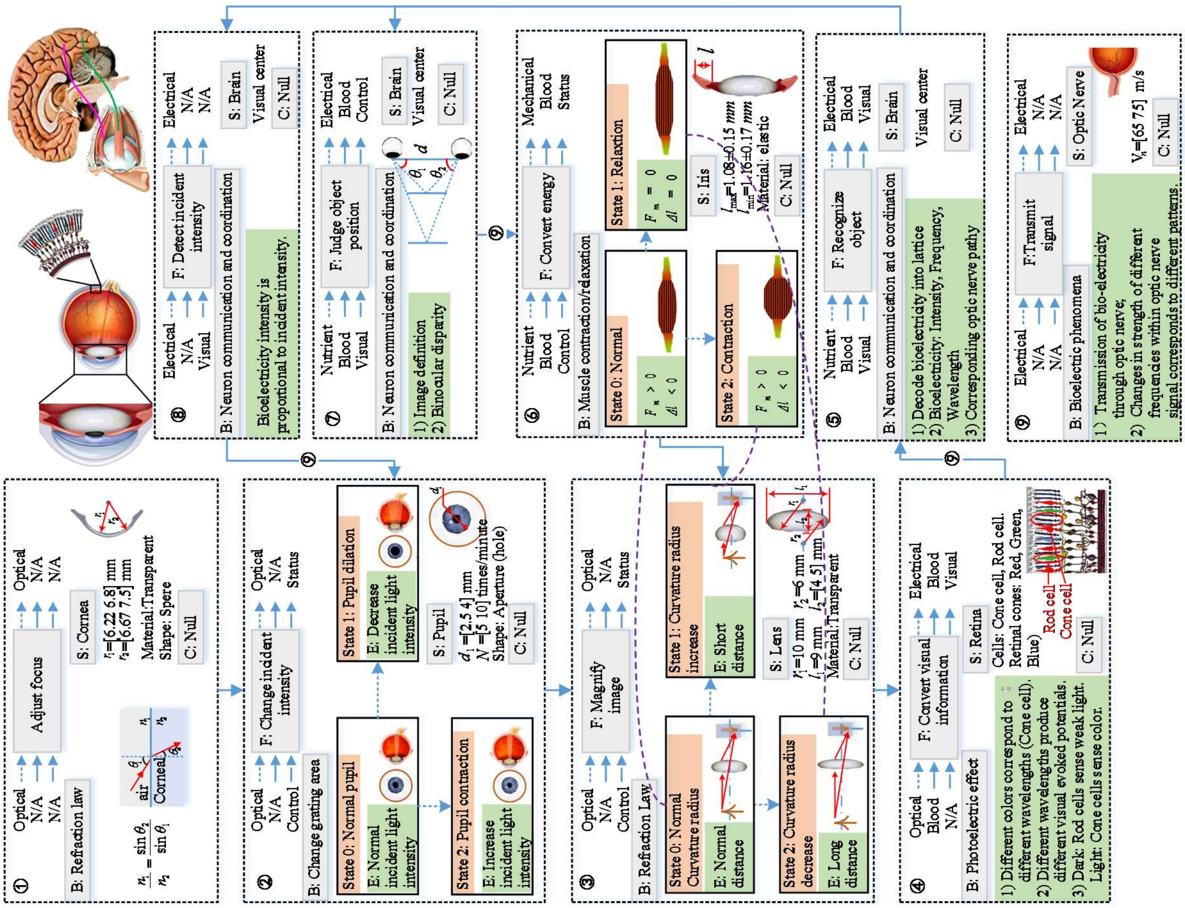

Figure 7. FBS knowledge cells derived from function decomposition of "form vision"

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