# Biologically Inspired Autonomous Mental Development Model Based on Visual Selective Attention Mechanism

**Sang-Woo Ban, Hirotaka Niitsuma and Minho Lee**

School of Electronic and Electrical Engineering, Kyungpook National University
1370 Sankyuk-Dong, Puk-Gu, Taegu 702-701, Korea
swban@palgong.knu.ac.kr, niitsuma@mub.biglobe.ne.jp, mholee@knu.ac.kr

### Abstract

We propose an autonomous mental development model that can voluntarily decide where and what it wants to see based on a bottom-up and top-down visual selective attention model in conjunction with human interaction. The proposed bottom-up saliency map model was developed by mimicking the functions of the visual pathway from the retina to the visual cortex through LGN. A low level top-down attention model implemented by a modified hierarchical Fuzzy ART network can incrementally inhibit uninteresting areas and reinforce interesting areas through human interaction. And a high level top-down attention model with human interaction for object non-specific representation and detection is proposed, which consists of a Gaussian mixture model and a maximum likelihood method for object representation and detection, respectively. The proposed model can generate a plausible attention map and give control signals to the effectors in robots to increase the machine intelligence through human interaction, autonomously.

## Introduction

Recent research efforts have been directed towards developing a more human-like machine that has an autonomous mental development mechanism. Weng et. al. described an autonomous development paradigm for constructing developmental robots as follows. First, we need to design a body according to the robot's ecological working conditions. Second, we need to design a developmental program. Third, at birth, the robot starts to run the developmental program. Fourth, to develop its mind, humans mentally must raise the developmental robot by interacting with it in real time (Weng et al. 2000). Scassellati considered the concept of theory of mind and theory of body to investigate models of social development (Scassellati 2003). Metta and Fitzpatrick conducted research related with integration of vision and manipulation and better vision through manipulation of something like active segmentation (Metta and Fitzpatrick 2003). Breazeal, who developed a humanoid robot 'Kismet,' has developed a model to express its emotion (Breazeal 1999). Biologically motivated systems have been proposed to overcome the limitations of conventional approaches in many engineering areas (Itti, Kock, and Niebur 1998, Koicke and Saiki 2002, Su and Fisher 2002, Ramstrom and Christensen 2002, Smeraldi 2000, Smeraldi and Bigun 2002). In order to develop a truly human-like machine, we need to understand well the functions of the human brain.

When we consider a human-like vision system for an autonomous mental development model, it is important that the human-like selective attention function can communicate with elements in the environment including a supervisor. Researchers such as Itti and Lee have suggested a bottom-up visual attention model that can generate a scan path for a visual scene based on mimicking the early human vision system (Itti, Koch, and Niebur 1998, Park, An, and Lee 2002). However, it is very difficult to understand the top-down visual signal processing mechanism in the human brain. The top-down visual attention mechanism has multiple levels that are developed through interaction with a human supervisor or environment. One is the low level top-down selective attention through inhibiting an uninteresting area and reinforcing an interesting area without considering whether the selected area contains objects or not. The other is the high level top-down selective attention, in which a human can pay attention to an interesting object according to one's interest or a given task. In order to develop an autonomous mental development model with a high-level top-down selective attention model, it is essential to have a mechanism that is able to automatically generate representation and indication for unknown interesting objects.

In this paper, we focus mainly on a vision system for an autonomous mental development model. We are developing an autonomous mental development system with various sensory systems including visual, auditory, and tactile like other systems such as DAV and SAIL at Michigan State University and Cog at MIT. However, the other parts of our system except for the vision model use simple and/or general methods. A new vision model is proposed to mimic the human-like selective attention mechanism not only with a bottom-up process but also with a process that ignores an unwanted area and/or pays attention to a desired area in the subsequent visual search process. In order to implement such a low level top-down trainable selective attention model, we use a bottom-up saliency map (SM) model in conjunction with a hierarchical fuzzy adaptive resonant theory (fuzzy ART) network. It is well known that the fuzzy ART model possesses the plasticity required to learn new patterns, while preventing the modification of patterns that have been learned previously (Carpenter et al 1992). We enhanced the conventional fuzzy ART model for our purpose by inserting human interaction mechanism (Choi 2004). Thus, the characteristics of unwanted salient areas and desired salient areas are obtained by the bottom-up saliency map model, and are used as input data of the hierarchical fuzzy ART model to incrementally learn and memorize feature information of unwanted areas and desired areas in a natural scene. The hierarchical structure in the fuzzy ART model offers a faster search process for finding a reinforcement area or an inhibition area in natural scene. The low level top-down model can ask a supervisor what the selected salient area contains, and then human supervisor can give knowledge to the autonomous mental development model. Then, the high level top-down model plays an important role for representing and indicating an arbitrary object. In order to develop such a high level top-down attention model, we use an object non-specific representation model based on a Gaussian mixture model and maximum likelihood method (Niitsuma 2004). Finally, the high level top-down model can indicate object information in natural scene, which can be used for object based autonomous mental development mechanism in robots.

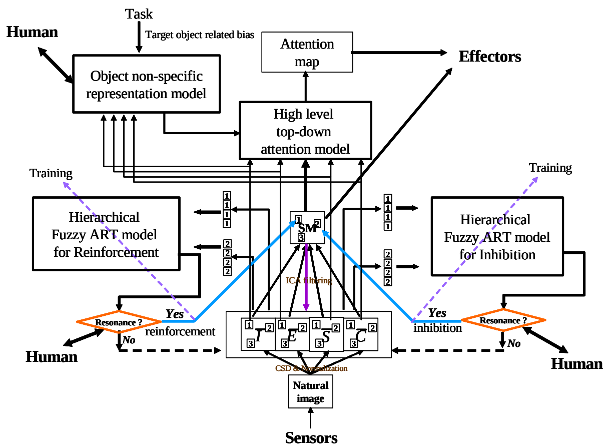
In the next section, we describe the proposed autonomous mental development model based on the visual selective attention and the object non-specific representation models. Computer simulation and experimental results will follow. The discussion and conclusions will be made in the final section.

## Autonomous mental development model

Each individual acquires its own characteristics in the course of communicating with and affecting from many persons. Like such a human developmental mechanism, we propose a vision based autonomous mental development model that can reflect a supervisor's preference to focus on an object in visual field by incremental learning process.

In order to develop such a developmental vision model, we need an intelligent model that can sequentially detect an interesting object in visual filed. The bottom-up saliency map model can be efficiently used for sequential search process as a preprocessor. In order to reflect the human's preference in the search process, we consider a low level top-down mechanism that modifies the visual scan path obtained by the bottom-up saliency map model through the interaction with human and environment. Using the bottom-up saliency map model and low level top-down attention mechanism, we can generate a candidate search region to find an interesting object. In order to develop an object non-specific representation and indication, we propose a Gaussian mixture model for each object that maximizes the likelihood of characteristics of an object. Through experience or exposure to objects in human interaction, the proposed model can generate an attention map for desired object detection based on a low level attention model and an object non-specific representation model like the human visual perception system. The generated attention map gives a control signal to the effectors such as a motor controller for the robotic systems and text to a speech module to make an appropriate action for human beings or environment. The bottom-up saliency map and low level top-down attention model also make the effectors to generate actions such as saccadic eye movement to generate a scan path.

In the following subsections, we describe a bottom-up saliency map model, a low level top-down attention model, an object non-specific representation model, and a high level top down attention model. Fig.1 shows the architecture of the proposed autonomous mental development vision model with visual selective attention function as well as human interaction.



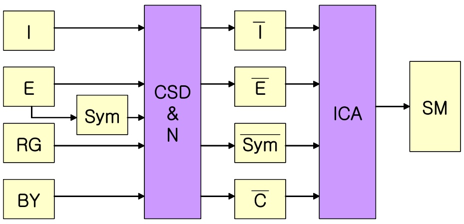

$\overline{I}$ : intensity feature map, $\overline{E}$ : edge feature map, $\overline{Sym}$: symmetry feature map, $\overline{C}$ : color feature map, ICA : independent component analysis, SM : saliency map

**Figure 1** The proposed biologically inspired visual selective attention model for an autonomous mental development model

### Bottom-up saliency map model

Fig. 2 shows our previously developed bottom-up saliency map model. In order to model the human-like bottom-up visual attention mechanism, we used 4 bases of edge (E), intensity (I), color (RG and BY) and symmetry information (Sym) as shown in Fig. 2, for which the roles of retina cells and lateral geniculate nucleus (LGN) are reflected in the previously proposed attention model (Park, An, and Lee 2002). The feature maps ( $\overline{I}$ , $\overline{E}$ , $\overline{Sym}$, and $\overline{C}$ ) are constructed by center surround difference and normalization (CSD & N) of 4 bases, which mimics the on-center and off-surround mechanism in our brain, and then are integrated by an ICA algorithm (Park, An, and

Lee 2002). In order to consider the shape information of an object, we consider the symmetry information as an additional basis. The symmetry information is obtained by the noise tolerant general symmetry transform (NTGST) method (Park, An, and Lee 2000). Independent component analysis (ICA) can be used for modeling the roles of the primary visual cortex for redundancy reduction according to Barlow's hypothesis and Sejnowski's results (Bell and Sejnowski 1997). Barlow's hypothesis is that human visual cortical feature detectors might be the end result of a redundancy reduction process (Barlow and Tolhust 1992), and Sejnowski's result is that the ICA is the best way to reduce redundancy (Bell and Sejnowski 1997). After the convolution between the channel of the feature maps and the filters obtained by ICA learning, the saliency map is computed by summation of all feature maps for every location (Park, An, and Lee 2002).




I : intensity feature, E : edge feature, Sym : symmetry feature, RG : red-green opponent coding feature, BY : blue-yellow opponent coding feature, CSD & N : center-surround difference and normalization, $\overline{I}$ : intensity feature map, $\overline{E}$ : edge feature map, $\overline{Sym}$ : symmetry feature map, $\overline{C}$ : color feature map, ICA : independent component analysis, SM : saliency map

**Figure 2** Bottom-up saliency map model

## Low level top-down attention model

Although the proposed bottom-up saliency map model generates plausible salient areas and scan paths, the selected areas may not be interesting because the saliency map is generated only by primitive features such as intensity, edge, color, and symmetry information. In order to develop a more plausible selective attention model, we need to develop an interactive procedure with human supervisor together with bottom-up information processing. Human beings ignore an uninteresting area even if it has primitive salient features, and can memorize the characteristics of the unwanted area. Humans do not pay attention to a new area that has characteristics similar to previously learned unwanted areas. Additionally, human perception can pay attention to an interesting area even if it does not have salient primitive features, or even though it is less salient than any other area. We propose a new selective attention model that mimics the human-like selective attention mechanism and that considers not only the primitive input features, but also interactive properties in the environment. Moreover, the human brain can learn and memorize many new things without catastrophic forgetting. It is well known that a fuzzy ART network can be easily trained for additional input patterns and also can solve the stability-plasticity dilemma in a conventional multi-layer neural network (Carpenter et al 1992). Therefore, we use a fuzzy ART network together with a bottom-up saliency map model to implement a low level top-down selective attention model that can interact with a human supervisor. During the training process, the fuzzy ART network learns and memorizes the characteristics of uninteresting areas and/or interesting areas decided by a human supervisor. After successful training of the fuzzy ART network, an unwanted salient area is inhibited and a desired area is reinforced by the vigilance value of the fuzzy ART network. The feature maps, which are used as input of the fuzzy ART network, have continuous real values. Thus, we considered a fuzzy ART network that can process the real values like ART 2 network. Moreover, the fuzzy ART network has a simpler structure than the ART 2 network and shows suitable performance for analog pattern clustering. As the number of training patterns increases, the fuzzy ART network becomes time consuming model to reinforce or inhibit some selected areas. For faster analysis to find an inhibition and/or a reinforcement area, we employed the hierarchical structure of the fuzzy ART network.

The hierarchical fuzzy ART network consists of a 5 concatenate layer structure in which each layer represents a different hierarchical abstract level of information (Choi 2004). The highest level of the model stores the most abstract information that represents a highly abstract cluster. The lowest level of the model stores more detailed information. Fig. 3 shows the architecture of the proposed trainable low level top-down attention model during the training process. Corresponding feature map information of the attention area obtained from saliency map is used as an input pattern of the hierarchical fuzzy ART model, and a human supervisor then provides the hierarchical fuzzy ART model with information whether it is a reinforcement area or an inhibition area. If the selected area is decided as an unwanted area, even though it has salient features, the inhibition part of the hierarchical fuzzy ART model trains and memorizes that area to be ignored in later processing. If the supervisor decides that the selected area should be reinforced, that area is trained by the reinforcement part of the hierarchical fuzzy ART model. After the training process of the hierarchical fuzzy ART model is successfully finished, it memorizes the characteristics of unwanted areas and desired areas. If a salient area selected by the bottom-up saliency map model of a test image has similar characteristics to the fuzzy ART memory, it is ignored by inhibiting that area in the saliency map or magnified by reinforcing that area in the saliency map. In the proposed model, the vigilance value of the hierarchical fuzzy ART model is used as a decision parameter whether the selected area is interesting or not. When an unwanted salient area inputs to the inhibition part of the hierarchical fuzzy ART model, the vigilance value becomes higher than a threshold, which means that it has similar characteristics to the trained unwanted areas. In contrast, of

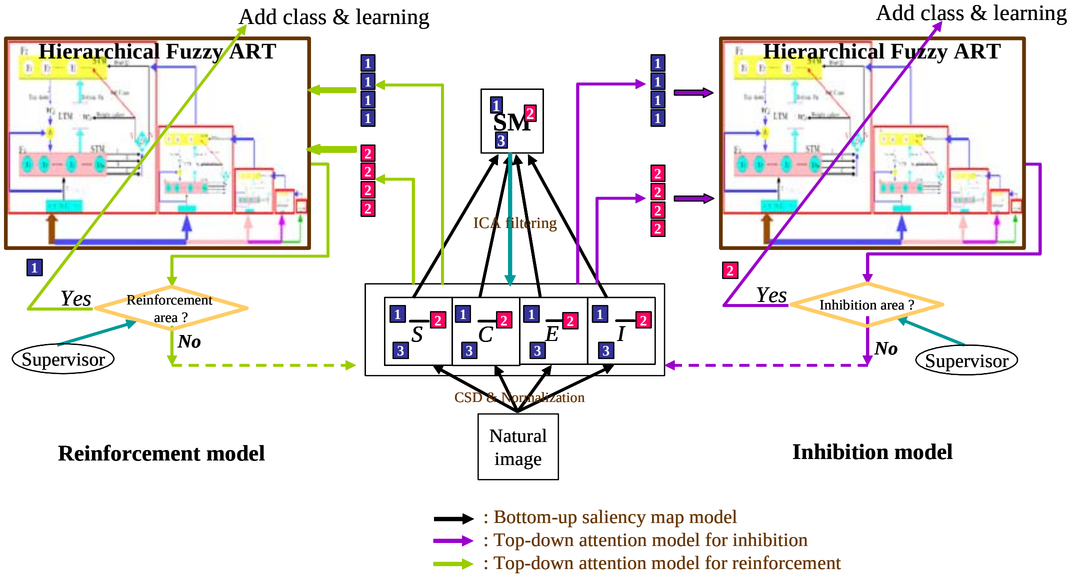



**Figure 3** The architecture of training mode of the proposed trainable selective attention model using hierarchical fuzzy ART network ( $\overline{I}$ : intensity feature map, $\overline{E}$: edge feature map, $\overline{S}$: symmetry feature map, $\overline{C}$: color feature map, ICA : independent component analysis, SM : saliency map). Square blocks 1 and 3 in the SM are interesting areas, but block 2 is an uninteresting area

the fuzzy ART model, the vigilance value exceeds a threshold, which means that such an area is interesting. As a result, the proposed model can focus on a desired attention area, but it does not pay attention to a salient area with unwanted features.

## Object non-specific representation model

One of the most important requisites of autonomous mental development is that it has a mechanism for a task non-specific process. In order to deal with a task non-specific process in vision model, object non-specific representation and detection is important for developmental model.

It is essential property that an object representation model gets robustness for affine transformation of an object. Appropriate parameter $\Phi$ of the affine transformation is estimated by maximizing the log-likelihood $\log P_{retina}(\Phi)$ in Eq. (1) (Niitsuma 2004):

$$\log P_{retina}(\Phi) = \int d\hat{t}\Lambda(\hat{t})\log p_{obj}(\hat{X}(\hat{t}) \mid \Phi) \qquad (1)$$

where the $\hat{\Lambda}(\hat{t})$ represents the weight function of sampling positions defined by the normal distribution function as shown in Eq. (2) that mimics the retinotopic sampling.

$$\hat{\Lambda}(\hat{t}) = \frac{1}{2\pi}\exp(-|\hat{t}|^2/2) \qquad (2)$$

In Eq. (1), $\hat{X}(\hat{t})$ represents characteristic information at every position $\hat{t}$ in an affine transformed input image and the function $p_{obj}(\hat{X} \mid \Phi)$ is the joint probability density function (pdf) as shown in Eq. (3):

$$p_{obj}(\hat{X}(\hat{t})) = p_{obj}(\hat{x}, \hat{y}, I(\hat{t}), \frac{\partial I(\hat{t})}{\partial \hat{x}}, \frac{\partial I(\hat{t})}{\partial \hat{y}}) \qquad (3)$$

in which $(\hat{x}, \hat{y})$ represents the affine transformed positions an $I(\hat{t})$, $\partial I(\hat{t})/\partial \hat{x}$, $\partial I(\hat{t})/\partial \hat{y}$ are the intensity and the intensity gradient features at the location $(\hat{x}, \hat{y})$, respectively.

We modeled the joint pdf $p_{obj}(\hat{X} \mid \Phi)$ as a Gaussian mixture model, which is determined by the vector of means $\varsigma$ and the covariance matrix $\Sigma$ as shown in Eq. (4):

$$p_{obj}(\hat{X} \mid \Theta) = \sum_{k=1}^{M} p_k N_5(\hat{X}; \varsigma_k, \Sigma_k)$$

$$\Theta = (\varsigma_1, \Sigma_1, \cdots, \varsigma_M, \Sigma_M) : a\ parameter\ of\ Gaussian\ mixture$$

$$N_l(z; \varsigma, \Sigma) = \frac{1}{\sqrt{(2\pi)^l |\Sigma|}}\exp(-(z-\varsigma)\Sigma^{-1}(z-\varsigma)/2) \qquad (4)$$

where $p_k$ represents a mixture weight of the Gaussian mixture model and $M$ is the number of variables of $\hat{X}$. The optimal Gaussian mixture model is obtained by the greedy expectation maximization algorithm.

We can construct a proper representation model for an arbitrary object using the proposed object representation model based on the Gaussian mixture model.

## High level top-down attention model

When humans pay attention to a target object, the prefrontal cortex gives a competition bias related with the target object to the infero-temporal (IT) area (Lanyon and Denham 2004). The IT area plays a role in object perception with object invariant representation mechanism based on the received bias signals. Then, the IT area generates target object specific information and transmits it to the high level attention generator that can conduct a biased competition and generate an attention map using both the object detection model and the results of the low level top-down attention model as well as the bottom-up saliency map model.

In this paper, we propose a simple high level top-down attention model that mimics the top-down attention function in our brain, which can generate an attention map using the object non-specific representation model and the object indication model based on maximum likelihood method and give control signals to the effectors.

A task for target object detection activates an object non-specific representation model for the target object. And then, the high level top-down attention model just compute the similarity of the statistical properties for current candidate search region based the object non-specific representation model and the object detection model using maximum likelihood, which can generate an attention map for the specific target object. Object detection can be considered as finding an appropriate mapped region in input image with an object model. Finding an appropriate mapped region is considered as finding the most proper coordinate transformation $\Phi$ in our object representation model. Thus, the high level top-down attention model can localize a target object by Eq. (5), in which a coordinate transformation that gives good agreement with the desired distribution $p_{obj}$ is a coordinate transformation which gives maximum likelihood.

$$\arg\max_{\Phi} P_{retina}(\Phi) \tag{5}$$

In the proposed model, we use the low level attention model in conjunction with the bottom-up saliency map model to decide a human-like selective attention region, and the results of saliency map is regarded as the sampling density $q(\hat{t})$ because we want to have much more sampled data in interesting area than that in uninteresting area. Suppose the features of an input image are sampled with the pdf $q(\hat{t})$. From the sampled results, $\log P_{retina}(\Phi)$ in Eq. (1) can be specified by Eq. (6):

$$\begin{aligned} \log P_{retina}(\Phi) &= \int d\hat{t} q(\hat{t}) \frac{\Lambda(\hat{t})}{q(\hat{t})} \log p_{obj}(\hat{X}(\hat{t}) \mid \Phi) \\ &\approx \alpha \sum_{n=1}^{N} \frac{\Lambda(\hat{t}_n)}{q(\hat{t}_n)} \log p_{obj}(\hat{X}(\hat{t}_n) \mid \Phi) \end{aligned} \tag{6}$$

where $N$ is the number of samples.

By considering relative important information for every region in an input image obtained from the saliency map, the high level top-down attention model can enhance the computational time owing to reducing the plausible candidate regions based on the saliency map to localize a target object.

In addition, the high level top-down attention model can provide informative control signals to the effectors, which can initiate another information processing process and make actuators to express something for human interaction in robot operation.

## Experiments

Fig. 4 shows the simulation results of the low level top-down attention model together with the bottom-up attention model. Fig. 4 (b) shows the scan path generated only by the bottom-up attention model. The numbers in Fig. 4 (b) represent the order of the scan path according to the degree of saliency. In Fig. 4 (b), the 4th and 5th salient areas are determined as inhibition areas by the human supervisor, which makes the hierarchical fuzzy ART network for inhibition train and memorize the characteristics of the 4th and 5th salient areas through modifying the weights. Three other interesting salient areas in Fig. 4 (b) are not decided as inhibition areas by the human supervisor. Fig. 4 (c) shows the generated scan path after the hierarchical fuzzy ART network for inhibition successfully trained the 4th and 5th salient areas in Fig. 4 (b). Moreover, if the human supervisor is mostly interesting in the 2nd salient area in Fig. 4 (c) than any other area, the human supervisor can make the hierarchical fuzzy ART network for reinforcement train and memorize the characteristics of the 2nd salient areas in Fig. 4 (c). After training for reinforcement of the 2nd salient areas, the proposed low-level top-down attention model can generate more plausible scan path, as shown in Fig. 4 (d). We experimented with many natural complex images to verify the performance of the proposed model. The proposed trainable selective attention model can successfully inhibit an unwanted area and reinforce a desired area through interaction with the human supervisor.

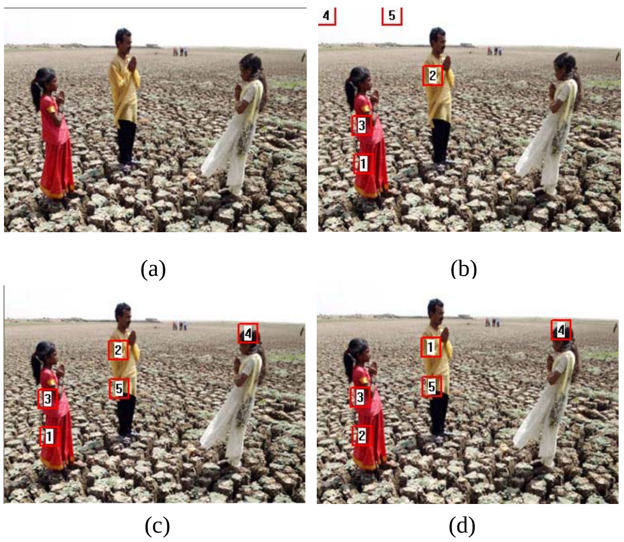
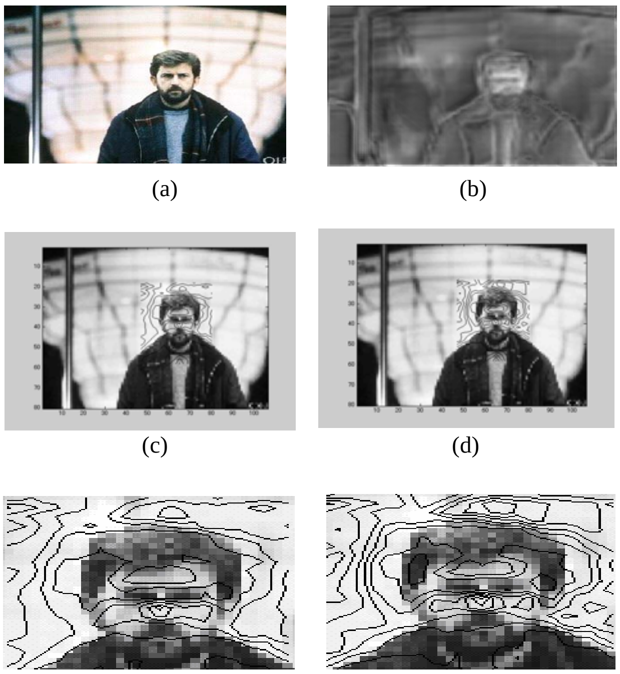



**Figure 4** Simulation results for bottom-up saliency map and low level top-down reinforcement and inhibition: (a) input image, (b) scan path generated by the bottom-up saliency map model, (c) scan path generated by low level top-down attention model after inhibition of the 4th and 5th salient areas in (b), and (d) scan path generated by the low level top-down attention model after reinforcement of the 2nd salient area in (c).

Fig. 5 shows the face localization results using the proposed the high level top-down attention model in conjunction with the bottom-up saliency map model and the low level top-down attention model. Fig. 5 (b) shows the bottom-up saliency map for the input image, Fig. 5 (a). The bottom-up saliency map model provides the high-level top-down attention model with the candidate search regions for object detection. And the face detection task activates the face representation model. Finally, the high level top-down attention model works for finding faces using the face representation model as well as a saliency map. As shown in Figs. 5 (c), (d), (e), and (f), we can get better performance to localize the human face by obtaining the sampling density $q(\hat{t})$ from the saliency map instead of using the uniform sampling $q(\hat{t}) = const$ . Although the model can localize the center of a face using uniform sampling, it also shows a very high likelihood of other areas such as above the head, as shown in Figs. 5 (d) and (f). Using the bottom-up saliency map model and low level top-down attention model as a preprocessor for face localization, we can not only reduce the computation time by small number of sampling points but also increase the localization performance to find an object.



(a) (b) (c) (d) (e) (f)

**Figure 5** The face localization results of the high level top-down attention model; (a) input image, (b) saliency map, (c) face likelihood result using the saliency map based sampling, (d) face likelihood result using the uniform sampling, (e) magnified face likelihood result of the face area in (c), and (f) magnified face likelihood result of the face area in (d).

We considered only the relative position information, the intensity information, and the gradient intensity as features for the proposed object representation model. However, we are considering an advanced model using more efficient feature information such as color or symmetry information. Moreover, we are developing an object discriminating model using SVM with Fisher kernel function instead of using the likelihood method to enhance the performance of the model. We are also constructing an autonomous mental development platform with various sensors mainly based on biologically motivated visual information processing mechanism.

## Conclusions

We developed a human-like visual attention model for a biologically inspired autonomous mental development model. Like the human vision system, at birth, the model knows very few things related with visual information. However through interaction with a human supervisor, it can incrementally learn and accumulate visual information and have its own preference about visual information. The proposed model can represent and discriminate more and more objects incrementally using both the object non-specific representation model using the Gaussian mixture model and the object detection model based on maximum likelihood method.

Our future research will develop an artificial office secretary with an autonomous mental development mechanism.

## Acknowledgement

This research was supported by the Brain Science & Engineering Research Program of the Ministry of Korea Science and Technology and grant No.R05-2003-000-11399-0(2004) from the Basic Research Program of the Korea Science & Engineering Foundation.

## References

Weng, J., McClelland, J., Pentland, A., Sporns, O., Stockman,I., Sur M. and Thelen, E. 2000. Autonomous Mental Development by Robots and Animals. *Science* 291: 599-600.

Scassellati, B. 2003. Investigating models of social development using a humanoid robot: In the proceeding of the International Joint Conference on Neural Networks, 2704-2709.

Metta, G. and Fitzpatrick, P. 2003. Early integration of vision and manipulation: In the proceeding of the International Joint Conference on Neural Networks, 2703.

Breazeal, C. 1999. Imitation as Social Exchange between Humans and Robots. In Proceedings of the 1999 Symposium on Imitation in Animals and Artifacts (AISB99), Edinburg, Scotland. 96-104.

Itti, L., Koch, C. and Niebur, E. 1998. A model of saliency-based visual attention for rapid scene analysis. *IEEE Trans.*

*Pattern Analysis and Machine Intelligence* 20 11:1254 - 1259.
Koike, T. and Saiki, J. 2002. Stochastic Guided Search Model for Search Asymmetries in Visual Search Tasks, *Lecture Notes in Computer Science 2525*, 408-417. Springer-Verlag, Heidelberg.
Sun, Y. and Fisher, R. 2002. Hierarchical Selectivity for Object-Based Visual Attention, *Lecture Notes in Computer Science 2525*, 427-438. Springer-Verlag, Heidelberg.
Ramström, O. and Christensen, H. I. 2002. Visual Attention Using Game Theory, *Lecture Notes in Computer Science 2525,* 462-471. Springer-Verlag, Heidelberg.
Smeraldi, F. 2000. Attention-driven pattern recognition, Ph. D. diss. Swiss Federal Institute of Technology in Lausanne.
Smeraldi, F. and Bigun, J. 2002. Retinal vision applied to facial features detection and face authentication. *Pattern Recognition Letters* 23 4:463-475.
Park, S. J., An, K. H. and Lee, M. 2002. Saliency map model with adaptive masking based on independent component analysis. *Neurocomputing* 49:417-422.
Carpenter, G. A., Grossberg, S., Markuzon, N., Reynolds, J. H. and Rosen, D. B. 1992. Fuzzy ARTMAP: A neural network architecture for incremental supervised learning of analog multidimensional maps. *IEEE Trans. on Neural Networks* 3 5:698-713.
Choi, S. B. 2004. Selective attention system using inhibition and reinforcement function at the saliency area. Ph.D. diss., Dept. of Sensor Engineering, Kyungpook National Univ..
Niitsuma, H. 2004. A non-parametric trainable object-detection model using a concept of retinotopic sampling. *International Journal of Computational Intelligence and Applications* 4 2:1-16.
Park, C. J., Oh, W. G., Cho S. H. and Choi, H. M. 2000. An efficient context-free attention operator for BLU inspection of LCD. *IASTED SIP*:251-256.
Bell, A. J. and Sejnowski, T. J. 1997. The independent components of natural scenes are edge filters, *Vision Research* 37:3327-3338.
Barlow, H. B. and Tolhust, D. J. 1992. Why do you have edge detectors? *Optical society of America Technical Digest* 23:172.
Lanyon, L. J. and Denham, S.L. 2004. A model of active visual search with object-based attention guiding scan paths. *Neural Networks Special Issue: Vision & Brain* 17 5-6:873-897.