System Integration for Intelligent Systems

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Abstract. The paper describes a model of system integration for designing intelligent systems. Systems for services and industries are expected to be coordinated internally and harmonized with the external environment and users. However, integration of the systems is difficult in general since the systems contain a number of processes with multiple tasks in different priority and timing. In this paper, we propose a model of system integration base on process categorization. We then validate the model based on dimension, hierarchy and symbolization comparing with case studies in the field of system intelligence. Discussion of the proposal framework will give us insight for designing interoperable infrastructures.

1 Introduction

System integration is a key issue for coordinating bunch of information in different levels of business scenes where the systems are expected to offer concentrated knowledge for workers in collaboration [12][4][5][2][10]. In a current stream of system intelligence, the system integration has been referred to as a main subject, since systems in the state of the art are required to realize continuous and smooth processing for integration, decision and implementation in task execution. However, the number of elements in recent systems is obviously increasing and the systems are getting more complex. Advanced methods of system integration are therefore desired for optimizing work flows and procedures in services and industries.

Problems in system integration include various issues such as efficient data handling and task priority control that should take care of human factors. In this paper, we focus on complexity in system integration. First, we will introduce categorization of processes in intelligent systems. We will then propose a model that integrates systems by coordinating different types of processes. We will compare the model with actually implemented systems in case studies and validate the proposed framework. The idea of the system integration is surely applicable for designing general structures of work flows and procedures in services and industries. Finally we will summarize the proposed framework and conclude an effective way to integrate systems.

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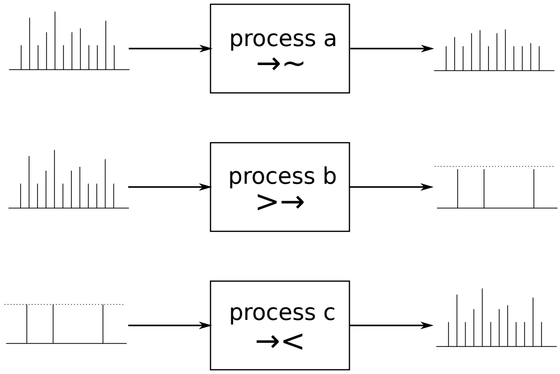


Fig. 1. Computation processes with different signal transformation. Process a, b and c show equivalent, simplificaiton and complication processes in signal transformation.

2 System Integration

We introduce types of computation process. Figure 1 shows three computation processes with different transformation between input and output signals. Process a, b and c in Fig.1 show signal transformation for equivalent, simplification and complication processes. These signal processes typically correspond to continuous modulation, pattern detection and pattern generation, respectively, in the field of system intelligence.

The following equations are respective examples of the process a, b and c in Fig.1:

$$y(t) = \sum_{\tau} x(t-\tau)h(\tau), \tag{1}$$

$$y(t) = \mathrm{step}(\sum_{\tau} x(t-\tau)h(-\tau) - \delta), \tag{2}$$

$$y(t) = \sum_{\tau} x(t-\tau)h_i(\tau), i = \mathrm{step}(\sin(2\pi t/T)), \tag{3}$$

where x, y and t denote input signal, output signal and time. h denote a function. Step function returns 1 or 0 if its argument is positive or anything else, respectively. These processes actually realize convolution-based impulse response, correlation-based pattern detection and switching pattern generation.

These signal processes can be integrated into more complex systems. Figure 2 shows a model of system architectures that allows integration, decision and implementation of signals coordinating with the external environment. Note that input-output transformation in the same level in Fig.2 corresponds to the equivalent process a, and input-output transformation to come up and down layers correspond to the simplification process and complication process in Fig.1, respectively.

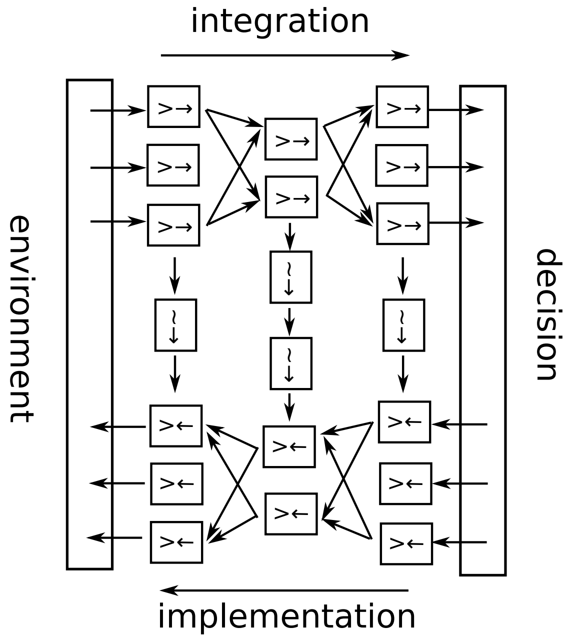
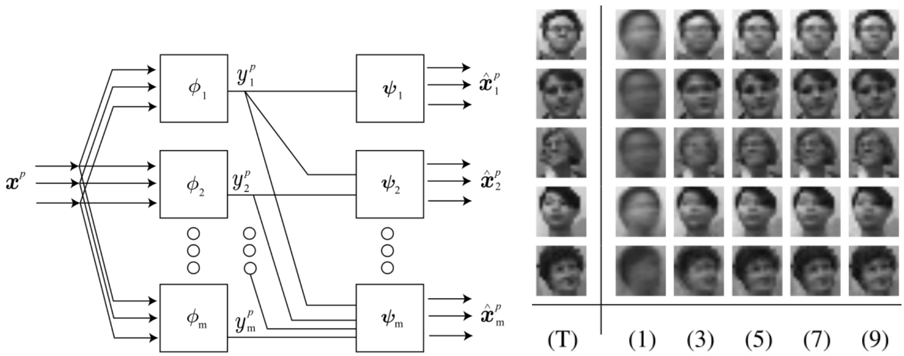


Fig. 2. A model of integrated systems. The model allows integration, decision and realization of signals coordinating with the external enviornment.

In order to handle huge information, a complex system should modulate quality of signals. In the environment side, signals are given from the environment where several events can occur independently. Signals from these events should be transformed into symbol patterns to concentrate information. In the decision side, signals can be sparse and tolerant for time and amplitude, while the number of patterns can increase because of the combinations. The symbol patterns can be evaluated for making decision. The decision is then implemented as continuous signal sequences that can actually affect for the environment. The signal flows through equivalent levels can function as shortcut pathways. The pathways allow prompt signal responses without waiting the results of higher level processes.

3 Case Studies

We will discuss system integration with three case studies in the field of system intelligence. Here we specially focus on the concepts of dimension, hierarchy and symbolization that appear in system architectures of the case studies. These concepts are surely important for designing complex intelligent systems. We will explain each concept in the following subsections.



(a) dimension reduction and recovery. (b) image reconstruction.

Fig. 3. Dimension reduction and recovery in nonlinear principal component analysis [9]. (a) a diagram of nonlinear pca. (b) reconstuction of 256 dimensional images from 1 to 9 dimensional data.

3.1 Dimension

Dimension gives a measure of data complexity. When data is represented as a vector, mathematical dimension of the data is defined as the number of the components of the vector. The data can be compressed by decreasing dimension, while the compressed data can be decompressed by recovering dimension.

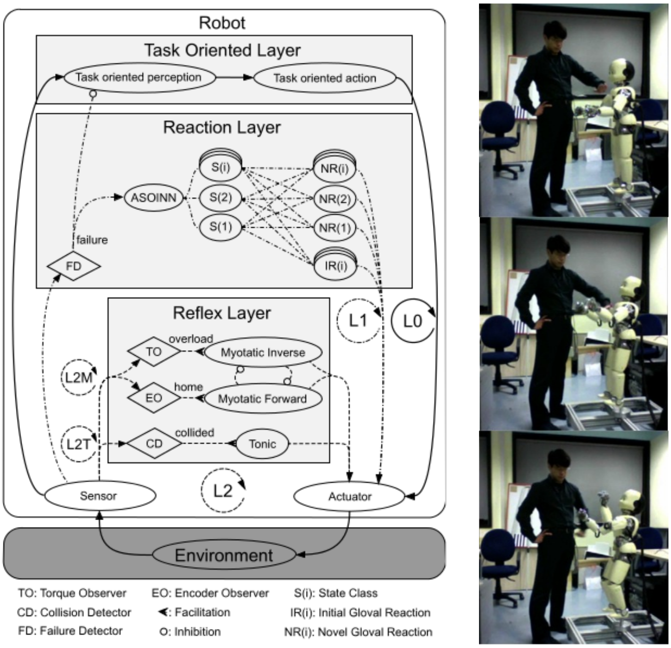
In the field of data analysis, principal component analysis (pca) is known as a standard method of linear data compression/decompression [3], while we developed a nonlinearized pca [9] that generalizes the conventional pca to allow nonlinear transformation as follows:

$$y_i = \phi_i(\boldsymbol{x}), \boldsymbol{z}_i = \psi_i(y_1, \cdots, y_i), \tag{4}$$

where $\boldsymbol{x} \in R^n$, $y_i \in R$ and $\boldsymbol{z}_i \in R^n$ are the input vector, ith nonlinear principal component and ith reconstruction vector. The set of functions $\{\phi_i, \psi_i\}_{i=1,\cdots,n}$ are given by minimizing the mean square error $\sum_j ||\boldsymbol{z}_i(\boldsymbol{x}_j) - \boldsymbol{x}_j||^2$. The data in n dimension can be represented in any lower dimension of $m \leq n$ by using the set of m nonlinear principal components $(y_1, \cdots, y_m)$.

Figure 3 shows dimension reduction and recovery with the nonlinear pca. Figure 3(a) depicts a diagram of the nonlinear pca that compresses and decompresses the data vector. Figure 3(b) shows image reconstruction by the nonlinear pca. The face images arranged in column T are 256 dimensional data. As shown in the figure, the 256 dimensional image data were represented in high fidelity with the principal components in 9 dimension.

In summary, dimension of data can be reduced and recovered by functions that are optimized to represent statistical features of the data set. Function ϕ_i and ψ_i



(a) hierarchical task structure. (b) protection

Fig. 4. A hierarchical task structure for whole body motor leaning of antrhopomorphic robots [11]. (a) a hierarchical task structure. (b) local force reflex that protects a joint from impact.

in the nonlinear pca acturally work as the simplification and complication processes in Fig. 1 respectively in terms of dimension control. This summary supports that process organization is important for systems to form signals in appropriate dimension.

3.2 Hierarchy

Hierarchy rules priority of system computation. In order to deal with important processes in high priority, the processes should be positioned in high layers of task hierarchy where the tasks are allowed to overcome the tasks in lower layers [1]. In the filed of system intelligence, self protection is an important task for agents working in the physical environment, since the agents need to be patient for physical damages in learning activity. The agents therefore should be able to protect the self in higher priority than other tasks.

Figure 4 shows a hierarchical task structures for whole body motor learning of anthropomorphic robots [11]. Figure 4(a) shows a hierarchical task structure that allows the robot to protect the self in higher priority during task leaning. Figure 4(b) shows force reflex that inhibits a whole body movement. During the movement, a joint in an arm limb detects unexpected force given by the experimenter and then triggered local reflex that loosed the joint in high priority to protect the joint from impact. Only the movement of the arm colliding with the experimenter was successfully inhibited, while the movements in the other limbs were kept on.

Independently from local force reflex, the robot generates self-protective reactions in high priority as shown in Fig. 4(a). We optimized the reactions base on head momentum M and joint load E as follows:

$$M = \sum_t |\omega(t)|, \tag{5}$$

$$E = \frac{1}{T} \sum_t \sum_i \dot{\theta}_i \tau_i(t) \delta t \tag{6}$$

where ω and t denote the angular velocity of the head and time. θ_i and τ_i denote the angle and torque of the ith joint in limbs. T and δt denote time duration of force impact and time step for sampling. The robot detects danger based on the head momentum and optimized the reactions to minimize the mean joint load.

In summary, the hierarchical task structure in Fig. 4 organizes local force reflex (L2 loop) and whole body reactions (L1 loop) to overcome general tasks (L0 loop). This task hierarchy actually implements signal pathways presented as vertical flows in Fig 2. These shortcut loops enabled the system to drive prompt actions (reflex and reaction in this case study) without passing time-consuming decision. The hierarchy of the system benefits also for temporal aspects.

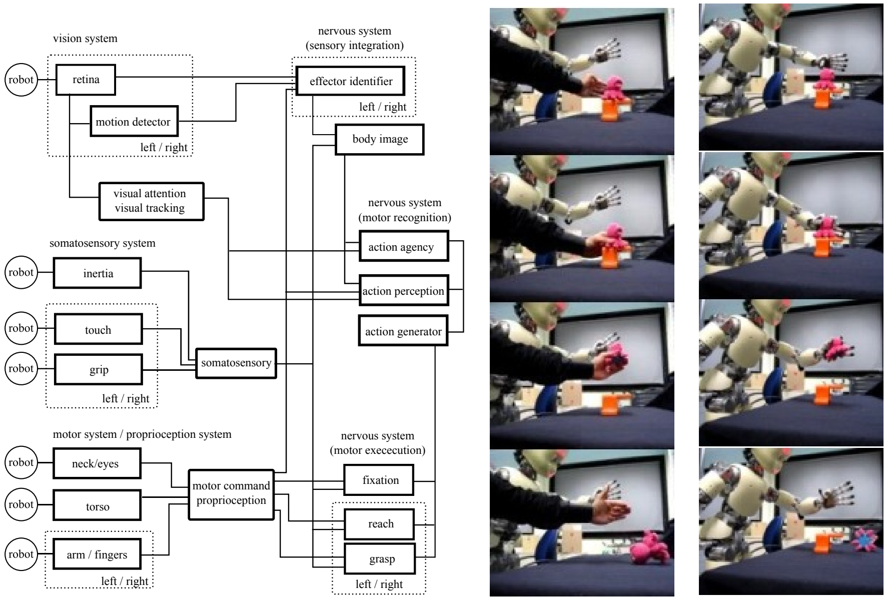
3.3 Symbolization

Symbolization makes a bridge between raw signals and semantic signals in biological systems [6]. Bio-inspired cognitive systems should also symbolize raw signals in sensor and actuator levels in order to realize efficient pattern recognition and decision making in higher levels.

Figure 5 shows a model of multi-modal signal symbolization and generation [7][8]. Figure 5(a) shows a model of developmental action perception system. The system firstly symbolizes features of an event perceived in multi-modal sensing. The system then decides a suitable behavior in motor repertory. The system finally realizes physical actions of the behavior by combining motor primitives that the robot learned in advance. Figure 5(b) and 5(c) show observation and reproduction of human actions, respectively, where reach, grasp, hold and drop actions were sequentially observed and reproduced by the robot. The time courses of the scenes are from top to bottom.

In decision levels after signal symbolization, the system associates an action symbol with a set of sensory symbols. After this learning, the system is able to estimate an action from observation based on the Bayesian estimation as follows:

$$\begin{aligned} &\hat{a}(E = (\cdots, e_i, \cdots)) \\ &= \arg\max_a \; p(A = a) \prod_{i=1}^{n} p(E_i = e_i | A = a), \end{aligned} \tag{7}$$



(a) developmental action perception system. (b) observation. (c) reproduction.

Fig. 5. A multi-modal signal symbolization and generation. (a) a developmental action perception system [7][8]. (b) observatoin of human actions. (c) reproduction of human actions.

where a, $\hat{a}$ and e_i denote the action symbol, estimated action symbol and sensory symbol of the ith sensory modality (vision, touch or proprioception), respectively. A and E are the corresponding probability variables. This estimation is done by the process of action perception presented in the right side (decision side) of Fig. 5(a). The estimated action symbol is embodied in the processes in sensor and motor layers.

In summary, the developmental action perception system in Fig. 5 symbolizes sensory signals, associates the sensory symbols with action symbols, and generates actual behaviors from the action symbols. These symbolization, association and generation correspond to integration, decision and implementation of the proposed system integration model in Fig. 2, respectively.

4 Conclusion

We discussed system integration for designing intelligent systems. We first categorized computation processes into three types of processes that correspond to equivalent, simplification and complication processes. We then proposed a general model of integrated system by combining the above-mentioned processes. The integrated system coordinates multiple processes by integration, decision and implementation of signals. We validated the proposed integrated system based on dimension, hierarchy and symbolization comparing with actually implemented systems in the field of system intelligence. In conclusion, we confirmed that the proposed model of process categorization and system integration generalizes case studies and gives insight in designing interoperable infrastructures for services and industries.

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