Object detection and representation in motivated conscious machines

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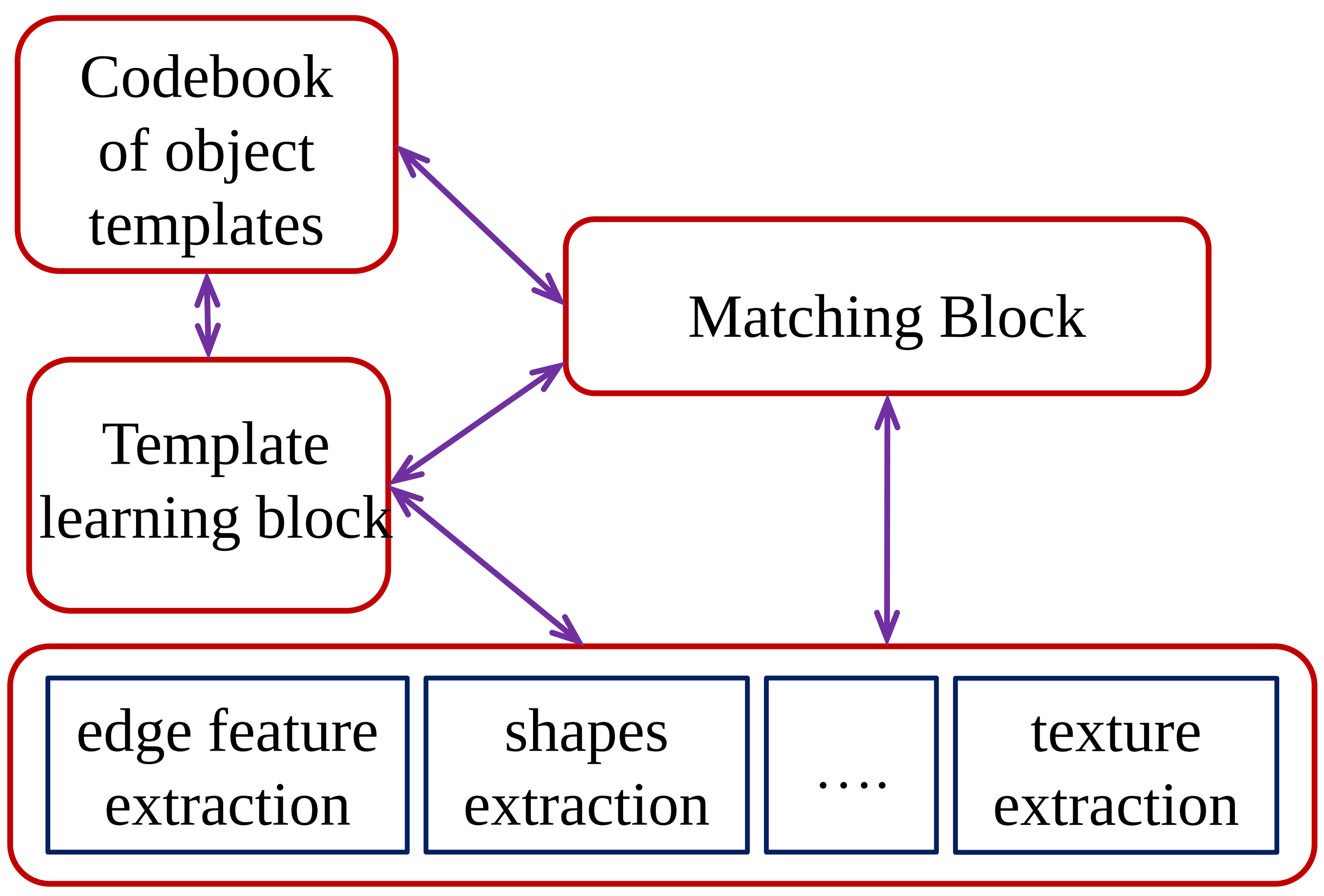
General Object Detection methods

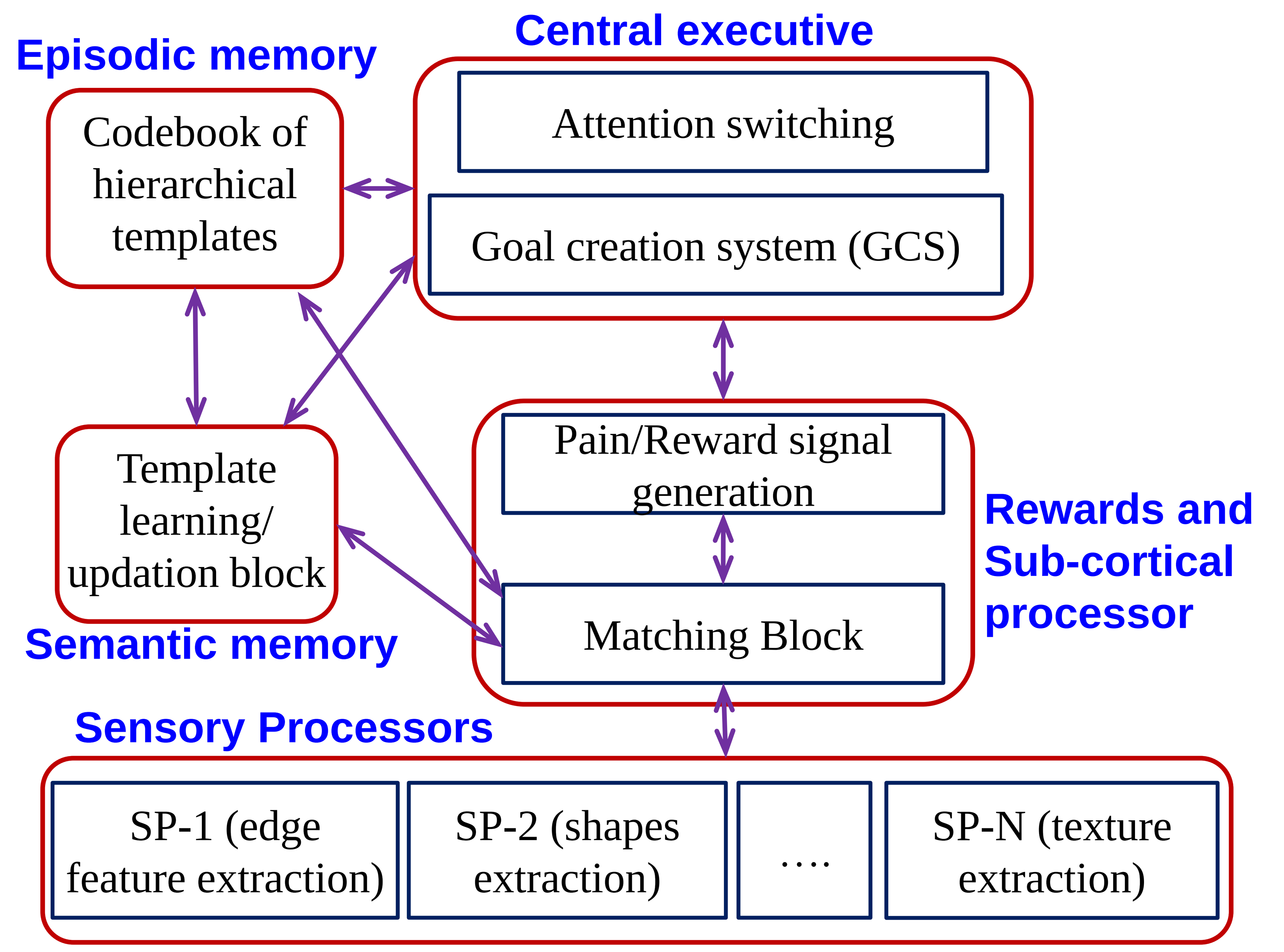
1. Target: intelligent and/or cognitive machines
2. Non-adaptive, fixed, and algorithmic approach : fixed thresholds, fixed parameters of matching algorithms, fixed learning algorithms and control parameters, fixed topology and maximum size of the object template
3. No use of intelligence or cognitive capability of the machine
4. Either generative learning or discriminative learning (not both)
5. Supervised learning - what to learn, from where, how to learn, how to validate, how to store (or represent) – all these are predefined by human designer (often based on heuristics) and fixed through the lifetime of the object detection execution.
6. Key features: scalability (within a certain range), invariance (limited)



General block diagram of contemporary object detection methods (on non-conscious machines)

Proposed object detection method for conscious machine

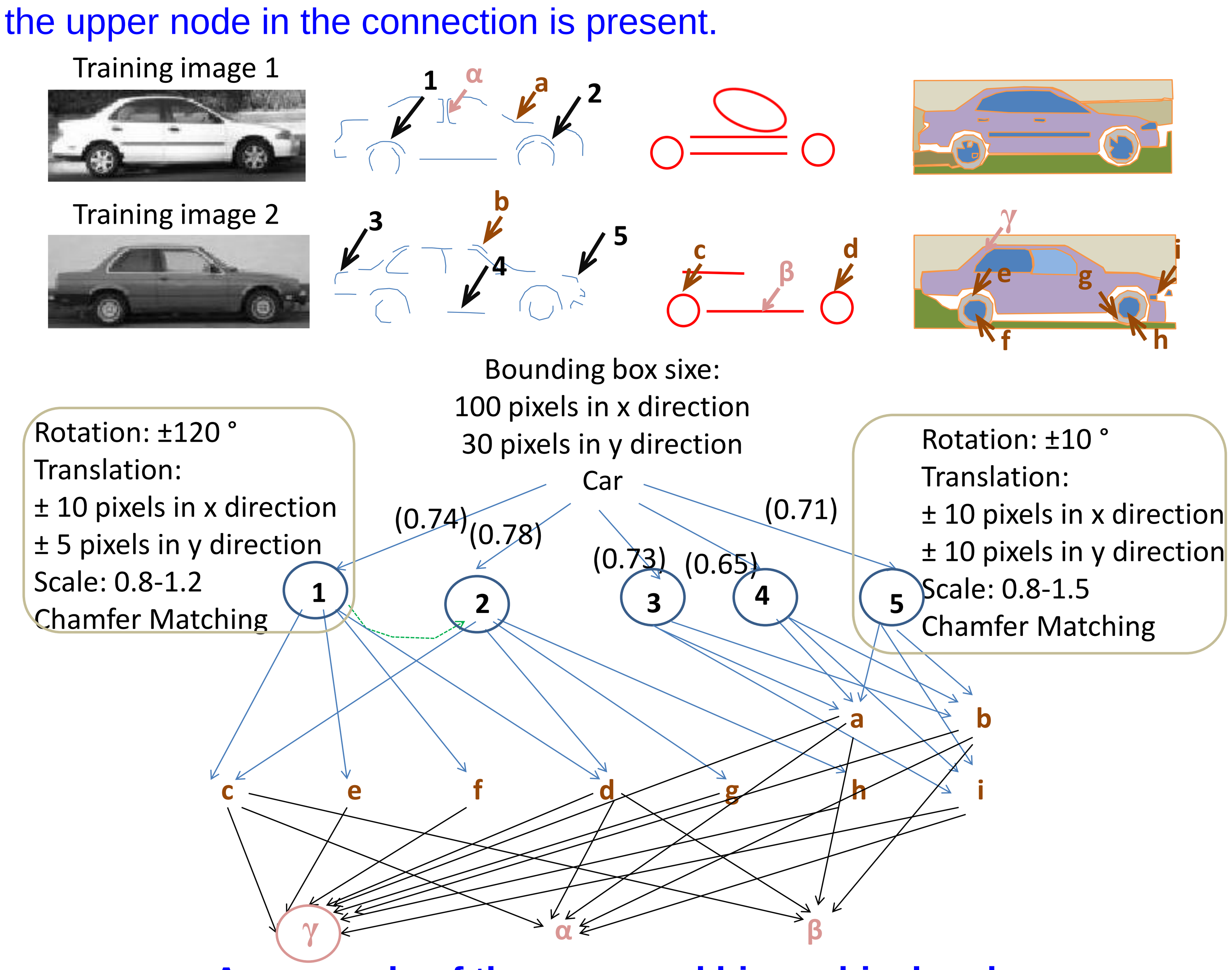
1. Target: intelligent machines (with motivation and consciousness [1])
2. Motivations help the machine in deciding goals of object detection and choosing suitable schemes for satisfying the current goals
3. Conscious agent can choose adaptively and dynamically : what objects are interesting, what features to learn, from where, using what learning scheme, how to accumulate and update its knowledge etc.
4. Machine develops its own heuristics, experience, preferences, etc.
5. Key features: unsupervised learning, scalability (machine decided), invariance (machine decided), anticipation, combination of generative and discriminative learning



Block diagram of the proposed computational model of object detection by a motivated conscious machine

Object representation: hierarchical object templates

- Most generic features (high likelihood) on top
- Lower level: more class specific or discriminative features
- Contents of each node: the feature, the type of feature, the type of matching technique, the type and amount of agility to be considered, and the likelihood ratio
- Weights of each connection: likelihood of presence of a feature given the upper node in the connection is present.



An example of the proposed hierarchical code

- The numbers 1-5 marked using large black arrows show the highest level in the hierarchical (most generic features).
- The alphabets a-i marked using medium brown arrows show next level of hierarchical code (which are more discriminative than upper level features).
- The Greek alphabets α-γ marked using small arrows show the lowest level in the hierarchical code.
- Each connection is given a weight that is equal to the likelihood of presence of a feature given the upper node in the connection is present.

- Good generative capability: each path in the tree is a representation of the object: object can be recognized even if one path is traversed
- Good discriminative capability: although the likelihood of lower level features may be low, but conditional to the presence of generic features, their likelihoods increase
- This implies that the simultaneous presence of generic and discriminative features is required to infer the class.

Impact of the proposed object detection methods

- Simple manner of incorporating dynamics and adaptivity. No complicated non-linear equations for steering the object detection method are required.
- Powerful in exploring various possibilities, learning various representations, choosing suitable parameters and learning methods (generative or discriminative learning).
- More realistic and wider range of detection/recognition may be incorporated.
- Such model is highly scalable. It is capable of learning not only new object categories, but also learning new features for existing object categories.
- Different level of discriminative capability (as the agent finds suitable) and generative capability may be used for different objects (depending upon the motivation and goals of the agent).

Dynamic updating of the exiting templates and learning from the test data is possible.

[1] J. A. Starzyk and D. K. Prasad, "Machine Consciousness: A Computational Model" Third International ICSC Symposium on Models of Consciousness, BICS 2010, Madrid, Spain, 14-16 July, 2010.
[2] J. A. Starzyk, "Motivation in Embodied Intelligence" in Frontiers in Robotics, Automation and Control, I-Tech Education and Publishing, Oct. 2008, pp. 83-110.
[3] D. K. Prasad and J. A. Starzyk, "A Perspective on Machine Consciousness" , Second International Conference on Advanced Cognitive Technologies and Applications, COGNITIVE 2010, Lisbon, Portugal, 21-26 November, 2010.