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Mind Operator: Zone-Associated Relative Representation

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1. Introduction

Since Chinese room argument was presented (Searle, 1980), a wide debate has run to discuss whether a machine could have mind. As Searle clarified, he had no objection to the claims of weak AI, but strong AI – that running the right sort of program necessarily results in a mind. Undoubtedly, the system passes the Turing Test but does not understand anything of its inputs and outputs. Whether there is mind in Chinese room depends on what mind means and whether machine could have human-like minds is not involved here. It is obviously that Searle and his objectors have different point of view on mind, which Wittgenstein clarified as “the picture of world” (Wittgenstein, 1974). Since “What can be said at all can be said clearly” (Wittgenstein, 1922), let’s make clear what on earth Chinese room says. Does the man in the room understand Chinese? It is definitely not. Does the whole room understand Chinese? The consensus stops here. Backward one step, we all agree that the whole room acts as it understands Chinese. What causes it? Does a system that has no knowledge of Chinese can operate Chinese rightly? Or can persons operate a car rightly without understanding the whole mechanism of the engine? We should distinguish the knowledge in different level, one is the ontological (or whole) knowledge, the other is part knowledge. Part originates from the whole. For certain application, we only need part knowledge. Return to the Chinese room, how if the master kindly equipped the man with a super Chinese-English dictionary, a hidden book that makes us trapped in controversy? This time, we find clearly that Searle differed from his objectors in whether sub knowledge is equivalent to the whole. Though in this point Searle is right, but because the difference can not be identified by outside observers and understanding can be viewed in different way, we had better to follow Turing’s way that “Instead of arguing continually over this point (machine thinking), it is usual to have the polite convention that everyone thinks” (Russell and Norvig, 2003). Final solution deeply depends on what we have mentioned above, i.e., what the mind is and what understanding means.

This chapter approaches mind problem in a new way. Based on latest study to outlier detection and some evidence in psychology and neuroscience, we give a framework to object representation and recognition problem. Because representation is the groundwork for recognition and the proposed representation (ART) has general basis, we call it mind operator. The principle that underlies ART is relativity, which has already made huge

success in physics but is still carefully avoided in other fields, being necessary to cause uncertainty. This is right what we need for computing – on probability. Therefore, so-called subjectivity, bridged by ART, gets to connect with the “machines”.

2. Intelligence

What's intelligence, or what's artificial intelligence? Historically, there are four categories (Russell and Norvig, 2003): Systems that think like humans, Systems that act like humans, systems that think rationally and systems that act rationally. Because rationality is related to humans, we actually only need the former two: Artificial intelligence is machines that think or act like humans. Another concept concerned is mind, intelligence is not enough for minds. Human beings are unwilling to acknowledge machines being of mind on the main reason that humans keep open to knowledge while machines cannot. Human beings are free to make mistakes and change mind, while machines are preprogrammed thus more seem to be determined beforehand. That is to say, human minds are in the process of probability events. The reason that current machine algorithm cannot be treated as human-like algorithm is that machines run definitely in a certain way while human beings do not. What's the special for human beings? Humans comprehend world by constructing relations among related events. Relationship is always experience-concerned, so our cognition is inevitably relative. Relativity is closely relevant to uncertainty. To realize uncertain computing, we can never rely on absolute way. There is an interesting new point of view to probability. Hutter (2005) argued that objective probabilities look somewhat “unscientific”, and thus do not exist. It is an outstanding idea, which was supported by recent studies to outlier (Hsiao, et al., 2008; 2009). The studies also indicate how many subjective factors make an object “objective”, which implies that relativity is the foundation of uncertainty. Physics tells us that quantum mechanics is truly random. It might be necessary so.

On the other hand, minds have to do with pattern recognition. An important task is to process noise. A good system should be robust to various noises. But in fact, noises are also pattern. The process of pattern recognition is also the process of outlier detection, vice versa.

2.1 Pattern and outlier

“A pattern is essentially an arrangement. It is characterized by the order of the elements of which it is made, rather than by the intrinsic nature of these elements.” (Gonzalez and Woods, 2008). Since pattern is a kind of order, outliers can be viewed as disturbers to the order. There are abundant patterns in nature, include noises. Traditional methods preprocess outliers before pattern recognition, which causes solution an ad hoc one. Since there is no general recognition algorithm, way to realize true intelligence is blocked. Reasonable approach is to treat outliers as patterns. Based on this idea, a robust solution was presented recently (Hsiao et al., 2009), where outliers, thus patterns are processed according to the breaking of consistence. Consistence can be viewed as symmetry, so no breaking, no pattern. Here we only give a definition of outlier to show the relation between outlier and patterns.

Definition: An outlier is an observation with a degree greater than a threshold in comparison with other observations referred to or associated with a specified pattern.

Outlier problem can finally be converted to classification of univariate dataset by Expanding Algorithm (Hsiao et al., 2009), which also means that pattern recognition in the end becomes the problem of numbers or the problem of relation of numbers.

2.2 Relativity

Application of relativity in physics is well known by the work of Einstein. General relativity has been accurately tested in the solar system (Hartle, 2003). This theory is currently the most successful gravitational theory, being almost universally accepted and well supported by observations. Besides, relativity also plays a very important role in economics. The influence was mainly exerted by Austrian School, where a subjective theory of value - marginalism was first introduced by Carl Menger (1871). When mentioning value of goods, Menger said, "The measure of value is entirely subjective in nature, and for this reason a goods can have great value to one economizing individual, little value to another and no value at all to a third, depending upon the differences in their requirements and available amounts... Hence not only the nature but also the measure of value is subjective. Goods always have value to certain economizing individuals and this value is also determined only by these individuals". Wittgenstein summed up the nature of relativity by a famous concept "family resemblance" (Wittgenstein, 1953/2001), which was believed to replace the Aristotelian idea of a certain set of attributes being common to all occurrences of a particular class (Osaka et al. 2007). In following section, a model based on relativity is built to describe patterns.

3. Relative Representation and Recognition

3.1 Associated Relative Representation

Recognition implies a match between two entities, and any theory of recognition must specify both the form of representation and the details of the matching process (Edelman, 1999). As brightness, color, texture are all less important than shape, main task of vision is to represent and recognize object's shape. Object recognition includes two categories. One is structure-based (Marr, 1982; Biederman, 1987) and the other is view-based (Poggio and Edelman, 1990; Bulthoff and Edelman, 1992). In contrast, structure-based will be more complex to derive, but will provide for less redundant storage (Bruce, 1988). Recent evidence from behavioural (Hummel, 2001; Foster and Gilson, 2002; Stankiewicz, 2002, Haywood, 2003; Thoma et al., 2004) and neuroimaging (Vuilleumier et al., 2002) studies suggests that view-invariant and view-dependent representations do co-exist in the brain with a relative preponderance that may depend on task, context and level of expertise. Thus generic part-based approaches like EBS approach (Martin Juttner, 2007) was presented, which is based on the notion that complex patterns are best encoded in terms of parts and their relations. Furthermore, an abstract framework for learning and recognition of objects was proposed (Wallraven and Bulthoff, 2007). The work was inspired by recent psychophysical results which have shown that object representations in the human brain are inherently spatio-temporal.

Indeed, if removing spatio-temporal relationship, there is nothing in a pattern. Furthermore, view-based or structure-based are not mutually exclusive. In essence, they should be associated with different weighting to become a complete solution. All atom unit (or

element) of patterns are all the same. Based on relativity, any pattern should firstly be self-expressed, which leads to the Associated Relative representation (ART).

Preliminaries

Let U denote a universe, Δ denote atom unit, and $\Lambda \subseteq U \times U$ denote spatio-temporal relations on U .

An arbitrary pattern $P \subseteq U$, could be expressed by a set of elements $p_1, p_2, \dots, p_m$ with a spatio-temporal structure. Any element p_i may be a Δ or a combined unit by atom units.

Representation

Given a pattern $P\{p_1, p_2, \dots, p_m\}$, which is in n -dimensional timespace, denoted by $\sum_n^m$.

For one kind of tempo-spatial relation, define a set R , denoting relations between any two elements, $R = \{r_1, r_2, \dots, r_\theta\}$, $\theta = m \times (m-1)/2$.

$$\forall i, j, k \ (i \neq j, i \neq k, j \neq k, 1 \leq i, j, k \leq m)$$

Let p_i and p_j construct a reference system with direction from i to j ($\vec{ij}$), and p_k be an evaluated element.

Convert the absolute relations to relative relations which could be expressed by a series of scalar quantity, $Q\{q_1, q_2, \dots\}$. Without loss of generality, we suppose scalar quantity ψ for one spatio-temporal relation.

Let ψ_k^{ij} expresses relative relation of k to i and j , then we can get a matrix for each i, j or k .

We call the following matrix evaluated matrix (E-mat) from the view of k , evaluated element;

$$\begin{bmatrix} \psi_k^{11} & \psi_k^{12} & \cdot & \cdot & \psi_k^{1m} \\ \psi_k^{21} & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \psi_k^{m1} & \cdot & \cdot & \cdot & \psi_k^{mm} \end{bmatrix}$$

A random specified value to ψ_k^{ij}
when $i=j$ or $i=k$ or $j=k$.

and following matrix from-matrix (F-mat) from the view of i ; to-matrix (T-mat) from the view of j .

F-mat:

$$\begin{bmatrix} \psi_1^{i1} & \psi_2^{i1} & \cdot & \cdot & \psi_m^{i1} \\ \psi_1^{i2} & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \psi_1^{im} & \cdot & \cdot & \cdot & \psi_m^{im} \end{bmatrix}$$

T-mat:

$$\begin{bmatrix} \psi_1^{1j} & \psi_1^{2j} & \cdot & \cdot & \psi_1^{mj} \\ \psi_2^{1j} & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \psi_m^{1j} & \cdot & \cdot & \cdot & \psi_m^{mj} \end{bmatrix}$$

Three types of matrices can be combined to a whole-matrix (W-mat). In this case, each element p_x ($1 \leq x \leq m$) is expressed from three aspects, evaluated, from and to. In application, distance and angle can be used for relations. All matrices form redundant information. The scalar quantity is a kind of code. For a example, to the three apexes of equivalent triangle, we can get a associated code: (1, 60°).

3.2 Zone-Associated Recognition

ART codes the region refer to each element. The scale of region is not limited. If fully chosen, a redundancy holographic information image is coded and no information is lost. The coded list can be used to recognize objects. Usually, region can be limited to a small zone around element, the zone can be treated as a structure. Combine all zones around each element, we get same relative complete representation. Recognition is just a process of comparing to prototypes. Here only full holographic expression is discussed. A possible simple matching algorithm is given as following.

Given a prototype $P(p_1, p_2 \dots p_m)$, and object $O(o_1, o_2 \dots o_l)$ in n -dimensional timespace.

1. Choose distance and angle as two associated relations.
2. For any element p_k in P and o_k in O construct two E-mat E_k and $E_{k'}$, whose element is the pair of distance ratio and relative angle like (r_{ij}, θ_{ij}) .
3. Define a similar function, $\text{sim}(E_k, E_{k'}) \rightarrow [0,1]$, denoted by $\text{sim}_{k'}^k$.
4. Define max zone match degree $\text{zmd}_{k'}^P = \max_k(\text{sim}_{k'}^k)$
5. Define whole match degree between P and O : $\text{wmd}_O^P = \sum_{k'=1}^l w_{k'} \times \text{zmd}_{k'}^P$, with weighting $w_{k'}$.
6. To multiple prototypes, choose one with max whole match degree as the recognition. Sometimes dual match is needed.
7. To weighting for all possible structure, similar method like tf and idf (Sparck, 1972; Salton and Buckley, 1988) can be adopted, which is experience related. Alternatively, recognition might also be a process of using Markov model.

4. Some evidence

4.1 Visual Illusion

Let’s first discuss about the length illusion. In Figure 1a, line a and line b have the same length, but a seems longer than b. The most often cited explanation is that one sees the lines as three dimensional, such as the outgoing and ingoing corners of a room (Gregory, 1968). Segall et al. (1963) argued that the Muller-Lyer illusion would only be perceived by those with experience of a "carpentered environment" containing numerous rectangles, straight lines, and regular corners. People living in Western societies live in a carpentered environment, whereas Zulus living in tribal communities do not. So Rural Zulus did not show the Muller-Lyer illusion, which demonstrates that Muller-Lyer illusion is experience-related and holistic. It means that lines should be represented as a whole with arrows and recognition is view-based, thus is concerned with probability. Such a explanation was also presented recently (Howe and Purves, 2005). All these can be realized well by the method proposed in this chapter.

Fig. 1. Visual illusions. (a) Muller-Lyer Illusion. The left line appears longer than the right one, although they are in fact equal in length (b) The Necker Cube: a wire frame cube with no depth cues (c) Kanizsa's Triangle. In which the eye perceives a white equilateral triangle where none is actually drawn (d) Pinna-Brelstaff Illusion. When observers look close or move away from the image keeping their eyes fixed on the center, the rings appear to rotate in the different directions

The Necker Cube (Figure 1b) is an ambiguous line drawing. It is a wire-frame drawing of a cube in isometric perspective, which means that parallel edges of the cube are drawn as parallel lines in the picture. When two lines cross, the picture does not show which is in front and which is behind. This makes the picture ambiguous; it can be interpreted two different ways. When a person stares at the picture, it will often seem to flip back and forth between the two valid interpretations. The effect is interesting because each part of the picture is ambiguous by itself, yet the human visual system picks an interpretation of each part that makes the whole consistent. The Necker Cube is sometimes used to test computer models of the human visual system to see whether they can arrive at consistent interpretations of the image the same way humans do. Humans do not usually see an inconsistent interpretation of the cube. A cube whose edges cross in an inconsistent way is an example of an impossible object, specifically an impossible cube.

There is evidence that by focusing on different parts of the figure one can force a more stable perception of the cube. The intersection of the two faces that are parallel to the observer forms a rectangle, and the lines that converge on the square form a "y-junction" at the two diagonally opposite sides. If an observer focuses on the upper "y-junction" the lower left face will appear to be in front. The upper right face will appear to be in front if the eyes focus on the lower junction (Einhauser, et al., 2004).

Two important points are concerned with Necker Cube. First, there are two interpretations; second, they cannot be observed at the same time. It shows that matching is necessary entity corresponded and there exists competition, which may be expressed by weighing of zone structure mentioned above with eyes moving.

Figure 1c was introduced by Gaetano Kanizsa (1955). Everyone sees a white triangle in front of the three black disks and inverted triangle. However, the white triangle does not exist. This effect is known as a subjective or illusory contour. Also, the nonexistent white triangle appears to be brighter than the surrounding area, but in fact it has the same brightness as the background. This illusion reveals the importance of subjectivity. Any minds are subjective. There is subjective objectivity, but difficult to make clear objective objectivity. In nature, this illusion reflects furthermore the significance of weighing coefficient, which determines how part can yield the whole.

To Figure 1d, when we stare at the black point and move our head back and forward, we feel rotating. Regardless of the mechanism of this Illusion, it is selected to show that illusive rotation is equivalent to real rotation to mind in case of same representation.

Four visual illusions are given, the phenomena indicates the general existence of relativity in our minds.

4.2 Synesthesia

Next, we discuss an experiment about synesthesia (Ramachandran, 2003), which was said a window into the nature of thought. We are mainly concerned with the mechnism of attention.

To synesthetes, Figure 2a will be like Figure 2b to us, so the triangle formed by 2 will pop-out to them. It shows synesthesia is a genuine sensory. In Figure 3a, if we stare at the small plus sign, we will find that it is easy to discern the number 5 off to one side. But if the 5 is surrounded by other numbers, such as 3's, then we can no longer identify it (Figure 3b). Big surprise is that to two synesthetes, "I cannot see the middle number. It's fuzzy but it looks red, so I guess it must be a 5." How can an "invisible" number produce synesthesia? So it must be visible to color feeling but invisible to shape feeling. This also indicates that reason of unidentification is not because things get fuzzy in the periphery of vision. After all, we could see the 5 perfectly clearly when it wasn't surrounded by 3's. We cannot identify it now because of limited attentive resources. The flanking 3's somehow distract our attention away from the central 5 and prevent us from seeing it. The experiment makes clear the importance of mechanism of attention before representation and recognition.

Fig. 2. (a) 2's amid 5's (b) 2's pops out for a synesthete

Fig. 3. (a) a single digit off to one side is easy to see with peripheral vision (b) number 5 is surrounded by others

Another contrast experiment was made in the same paper. When we reduced the contrast between the number and the background, the synesthetic color became weaker until, at low contrast, subjects saw no color at all, even though the number was perfectly visible. That is, whereas the crowding experiment shows that an “invisible” number can elicit color, the contrast experiment conversely indicates that viewing a number does not guarantee seeing a color. They are actually all attention problem that we will mention later.

4.3 Neuroscience

Recently, as the discovery of synchronous oscillation in the visual cortex, some hypothesis and models were presented (Fujii et al, 1996; Watanabe et al, 2001; Zhao et al, 2003). Synchronous oscillation can be thought as a mechanism of attention and could be combined with ZART easily.

Every object is expressed by elements with relations of each other. Each element could be expressed by a matrix, or a series of numbers, which may be the codes being discovered by Lin et al (2006). Combined with ϑ algorithm (Hsiao et al., 2009), a method can solve outlier problem at the same time when object is identified, ZART might become more robust. There is also evidence for ϑ algorithm. Recent study also shows that traditional view that figure-ground segregation precedes object recognition may not be right, and though their data cannot determine whether the extra time needed for identification compared to categorization reflects the engagement of a different mechanism or simply a longer engagement of the same mechanism involved in categorization (Kalanit Grill-Spector and Nancy Kanwisher, 2005). They believe it is possible that the initial neuronal responses are sufficient for detection and later neural responses are necessary for identification.

Latest study found that concept and knowledge have its neural encoding in the mouse brain (Lin et al. 2007). From the view of ZART, a concept is something that origins from the common of the same type of objects experienced. In detail, a concept is the common elements and their relations of that type. Undoubtedly, concept can be encoded.

The study presents a feasible model. Our brain may not be complete same as the model, but since what we focus on is to realize mind, we are not required to keep same with the real brain.

5. Natural Classification

As discussed above, attention should be exerted before representation and recognition (mutual case may exist), which is a process of natural classification. An ontological classification method - Expanding Algorithm can be employed to solve this problem. Some applications are accounted as following.

5.1 Cornsweet Illusion

The Cornsweet illusion shown in Figure 4 is an optical illusion that was described in detail by Cornsweet (1970). In the image, the entire region to the right of the "edge" in the middle looks slightly lighter than the area to the left of the edge, but in fact the brightness of both areas is exactly the same, as can be seen by blacking out the region containing the edge. Purves et al. (2002) gave an explanation of this illusion on an empirical basis. In their words, "...[perception] accords not with the features of the retinal stimulus or the properties of the underlying objects, but with what the same or similar stimuli have typically signified in the past".

Fig. 4. Cornsweet illusion. Left part of the picture seems to be darker than the right one. In fact, there have the same brightness.

Explanation based on experience is always effective. While in this case, it is a simple classification problem based on mind, which can be solved easily by Expanding Algorithm. Different values of gray scales could be expressed by one dimensional data sets, major brightness in this image is 173 (0 is black and 255 is white), values of two sides are listed by pixel as a set $C\{173, 172, 171, 170, 169, 168, 167, 178, 177, 176, 175, 174, 173\}$. The narrow band from 172 to 167 and 178 to 174 in the middle brings different bright feeling to same most 173s on both sides.

By running Expanding Algorithm to set C , we can divide them into two parts easily. One part is from 173 to 167, 178 to 173 is the other. Though there might be other complicated mechanism in visual system, such division is enough. Mind has to make a distinction, the key is in where. All perceptible things are related to Expanding Algorithm, which is a basis algorithm of mind. There is no absolute division like all 173s should be felt same, it depends. We consider another example where more than two classes are involved. Used data is Ruspini dataset (Index, 2009).

5.2 Multiple Classes

The Ruspini dataset consists of 75 points (Figure 5) in four groups, which is popular for illustrating clustering techniques (Ruspini, 1970). Clustering is one of the classic problems in machine learning. A popular method is k-means clustering (Lloyd, 1982; Arthur and Vassilvitskii, 2007). Although its simplicity and speed are very appealing in practice, it offers no accuracy guarantee. Furthermore exactly solving the problem is NP-hard (Drineas, et al, 2004). Like k-means, most algorithms use center to represent a cluster, each element is classified according to the distance between it and its closest center. Real case is not always so. According to recent studies (Hsiao et al., 2008; 2009), absolute center is not necessary. “Family resemblance” also demands us to throw away the concept of center (it doesn’t mean that center is useless). Based on these theories, a new method is presented to cluster Ruspini data.

Fig. 5. Ruspini data (five clusters by Oscillator Algorithm)

Given Ruspini data sets $D \{d_1, d_2, \dots, d_{75}\}$ with each point as a cell.

Oscillator Algorithm:

1. Calculate distances between any two points d_i and d_j .
2. To any point d_i , arrange its distance series (with others) in ascending order.
3. Calculate series of any i by Expanding Algorithm (Safest point is the first one and at least including three points for more than two classes exist). Getting 75 clustering sets.
4. Random choose one point as a seed with firing intensity 1 (others 0).
5. Any partner (clustering member) of the firing cell can receive its stimulus thus begin to fire with same intensity, others receive an identical negative input.
6. Repeat step 5 till all cells keep same or are full charged (include negative charged).
7. To all cells with positive firing, cluster them to one.
8. Choose rest points, repeat from step 4 to step 7.
9. Alternative approach: combine all the results of each cell, determine clusters.

Cluster	Included Elements	Number of elements with right clustering	Silent elements	Probability for right clustering
1	1-20	18	17, 20	90%
2	21-43	21	41, 42	91%
3	44,45,49-60	11	44,45,58	79%
4	46,47,48	2	46	67%
5	61-75	15	-	100%

Table 1. Clustering summarization from the view of each element

Figure 5 shows the clustering condition by Oscillator Algorithm. The data are clustered into five. Considering the small scale of cluster 4 (46-48), we can easily merge it with its nearest neighbor - cluster 3. In that case, result keeps same with the designed. But if there is no extra information or restrict, cluster 4 can also be treated as outlier. Table 1 lists a detailed result by Oscillator Algorithm. Each cell was chosen as seed in turn, two kinds of results were achieved. One matches the result of five clusters, in the other case, cells keep silent, it means corresponding cell had no way to call a resonance. The result appears positive, furthermore, it is totally based on uncertainty- that is what we need for mind.

6. Related Work and Discussion

For object recognition, good method should be robust to noise. Hough Transform is such a technique. Developed by Hough (1962), the transform consists of parameterizing a description of a feature at any given location in the original image's space. A mesh in the space defined by these parameters is then generated, and at each mesh point a value is accumulated, indicating how well an object generated by the parameters defined at that point fits the given image. Mesh points that accumulate relatively larger values then describe features that may be projected back onto the image, fitting to some degree the features actually present in the image. The classical Hough transform was concerned with the identification of lines in the image, later the Hough transform has been extended to identifying positions of arbitrary shapes (Duda and Hart, 1972; Ballard, 1981), called Generalized Hough Transform (GHT).

Although the GHT is optimal for an object that has undergone simple translation, it is far less efficient when an object has also undergone rotation and scaling. Chord-Tangent Transformation (CTT) was thus presented (Dufresne and Dhawan, 1995). The method exploits a simple relationship existed between tangent points and chord lines which allow a transformation which is invariant to rotation, translation and scale. The C-table designed has many similarities to the R-table of the GHT, yet differs in the gradient for index. The GHT uses the absolute gradient of the tangent, while the CCT uses two relative measures of the gradients of a pair of tangents. It is such relativity that guarantees the invariance, which is awfully important in object recognition. In contrast, ART is completed based on relativity. Another relativity-related tool for object recognition is the shape context (Balongie, et al, 2002), which has been shown to be a powerful one. The shape context is a descriptor to each point in a shape, which captures the distribution of the remaining points relative to it thus offering a globally discriminative characterization. Corresponding points on two similar shapes will have similar shape contexts; the dissimilarity between two shapes is computed as a sum of matching errors between corresponding points, together with a term measuring

the magnitude of the aligning transform. The recognition is treated as the problem of finding the stored prototype shape that is maximally similar to that in the image.

ZART has many similarities to the shape context, both have a global descriptor to each point, both try to find corresponding match, both compute dissimilarity between two shapes by a sum of matching errors, both should solve problem of prototype shape. But there exists obvious difference. The shape context is like the original Chinese Room, where many persons do not see mind, while ZART is designed for mind, being of redundant structural knowledge.

Another important technique should be mentioned is AdaBoost, short for Adaptive Boosting, which is formulated by Freund and Schapire (1997). Boosting is a general approach to improve of a given classifier and is one of the most powerful techniques, together with the support vector machines (Theodoridis and Koutroumbas, 2006). The roots of boosting go back to the original work of Viliant and Kearns (Viliant, 1984; Kearns and Viliant, 1994), who posed the question whether a “weak” learning algorithm (i.e., one that performs just slightly better than a random guessing) can be boosted into a strong algorithm with good error performance. The answer is very impressive indeed. The final classifier is obtained as a weighted average of the previously hierarchically designed classifiers. It turned out that given a sufficient number of iterations the classification error of the final combination measured on the training set can become arbitrarily low (Schapire, 1998). Sense of AdaBoost is great: the best is not necessary thus does not exist, there are no magic recipes, and the underlying principle might be relativity. AdaBoost, $\exists$ algorithm and the Chinese Room all imply that syntax is enough for intelligence, does mind really make sense?

Face recognition was thought to be “special” and differ from other object recognition (Farah et al. 1998) in “holistically” (i.e., using relatively less part decomposition than other types of objects). But such distinction does not make significant sense since it is a problem of less and more. Early research by Phodes (1988) indicated that both first (local, i.e. eye, nose, and so on.) and second order features (configurational, i.e. spatial relations among first order features and the position of first order features, along with information about face shape.) were relevant determinants of facial appearance. Up to latest studies, there is no change to it as Khashman (2008) reviewed, “One common concept that is shared by most methods is that the detection of a face requires facial information, which can be obtained locally (using local facial features such as eyes) or globally (using a whole face)”. The reason that we use more holistic feature is just that the local one does not work. There is no changeless pattern for mind. Codes are all in ZART, the other work is just mining.

7. Conclusion and Future Work

This chapter proposed a framework to mind problem. A Zone-Associated Relative representation (ZART) was presented for objects. Corresponding method for recognition was also accompanied. Some evidence in psychology and neuroscience was reviewed to support the proposal. Besides, a novel Oscillator Algorithm based on Expanding Algorithm was introduced to simulate the visual mechanism of attention, which is a process pre-head of representation and recognition. Related work has been compared carefully. The whole work was approached from a new one. Algorithms were constructed on uncertainty, which was argued to be necessary to a mind.

Since Feigenbaum formulated the hypothesis about the power of domain-specific knowledge (Feigenbaum, 1977), a great deal of experiments have been done and strongly supported the view. "The power of AI programs to perform at high levels of competence is primarily a function of the program's knowledge of its task domain, and not the program's reasoning processes" (Feigenbaum, 1996). Knowledge-based system is in essence a relative system. The simplest knowledge representation is a kind of rules like the Chinese Room (even the worst knowledge is better than logic), where intelligence appears rather well. But we expect more.

Before we leave the Chinese Room, we have to reach a conclusion. Understanding is to build relations between outside and outside or outside and inside, and mind is to represent and yield understanding. Degree of comprehension is hierarchy of relations. In this way, it is obvious that Searle's Chinese Room is not of "mind" indeed. No representation, no mind. Very recently, Hamlin et al. (2007) reported that 6- and 10-month-old infants showed crucial social judging skills before they could talk, which does not stem from infants' own experiences with the actors involved. If it is true, we have more to do.

Future work includes further research to ZART and its application in AI, new neural network model and information retrieval. Parallel work includes psychological study to mind.

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