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A Brain Inspired Approach for Multi-View Patterns Identification

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Abstract—Biologically human brain processes information in both unimodal and multimodal approaches. In fact, information is progressively abstracted and seamlessly fused. Subsequently, the fusion of multimodal inputs allows a holistic understanding of a problem. The proliferation of technology has exponentially produced various sources of data, which could be likened to being the state of multimodality in human brain. Therefore, this is an inspiration to develop a methodology for exploring multimodal data and further identifying multi-view patterns. Specifically, we propose a brain inspired conceptual model that allows exploration and identification of patterns at different levels of granularity, different types of hierarchies and different types of modalities. A structurally adaptive neural network is deployed to implement the proposed model. Furthermore, the acquisition of multi-view patterns with the proposed model is demonstrated and discussed with some experimental results.

Keywords—Multimodal, Granularity, Hierarchical Clustering, Growing Self Organising Maps, Data Mining

I. Introduction

IT has been proven that the human brain, particularly the cerebral cortex, consists of many hierarchical models. For instance, visual cortex, cortical columns, and etc. have shown the structure of hierarchies in the human brain [1], [2]. In addition, the different layers at the standard areas of cortex have also shown the characteristic of granularity. It has also been reported that synaptic dynamics of neurons at different levels of layers (granularities) in charge of the forward and backward connections as well as the intrinsic and extrinsic connections of the cortical regions [3]. Similarly, the multimodality of human brain could be observed at the association areas of the cerebral cortex. In fact, input signals are first processed unimodally or individually. At higher hierarchical level, these unimodally processed signals are subsequently integrated and associated at association areas for purposes such as coordination of movements, cognitive capabilities, and so on [1].

In order to survive, humans have evolved the capability to use multiple senses naturally to identify, assess and evaluate objects, patterns, events and environments around them and most importantly to protect themselves [4]. Henceforth, human brain is constantly integrating multiple senses in the state of multimodality. In other words, we could say that human brain is effectively and efficiently abstract and fuse various input sources (modalities of data) seamlessly during the processes of pattern recognition and identification. In addition, we do not simply understand the world by processing inputs in single level (flat) and isolated mode. We always organise worldly things in hierarchical structures and look at them at different levels of granularity for the acquirement of multiple views [5]–[8]. In fact, we have the capability to switch easily from multiple views and at different levels of granularity [5]. Similarly, [9] has argued and discussed about the fact that human has “Ways to Think”in which we could represent things in many different ways.

The proliferation of technology has exponentially produced various sources (or modalities) of data, which could be likened to being the state of multimodality in human brain. Specifically, the accummulations of multiple modalities of data is common issue encountered in the field of Data Mining. When multiple data sources are involved in a data mining problem, the existence of multimodality should be realised and taken into consideration. That means, for a given application domain, the related data sources could be regarded as various modalities in relation to its context of the domain. For instance, data mining in medical domain could involve different modalities of data, such as patients, pathology, X-rays, etc. In fact, we could retain the structures and properties of these data without integrating them into an integrated database.

By presenting a data mining problem with multimodality, this motivates us to explore different modalities of data and identify patterns unimodally and multimodally. For a unimodal pattern explorations and identifications, this allows unimodal patterns to be explored at different levels of granularity or abstractions. In fact, the patterns that exist at different levels of granularity could be represented in hierarchical structures, such as concept hierarchies. Thus, the combinations of patterns from several unimodal explorations have created the associations of patterns across several modalities. Such pattern identification approach emulate the three characteristics of human brain, namely Hierarchy, Granularity and Multimodality in human brain.

Normally, the integration of all data into a mono-database is the common approach and has been widely adopted for pattern mining. Nevertheless, this approach may lead to two possible problems, as discussed in [10]. Firstly, it is possible that certain patterns have been destroyed during the integration process. Secondly, certain patterns, espcially some trivial ones, could still remain hidden. Due to these reasons, it is vital to have an approach that could identify patterns from different levels of abstractions and simultaneously maintain structures and properties of these data. Hence, this highlight the need of

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developing a brain inspired approach for pattern identifications that portray the three properties in human brain.

Given that various sources (or modalities) of data are considered in a data mining problem, it is highly desirable to construct a conceptual model that capture and emulate the three key characteristics in human brain for pattern identifications. With regards to this objective, the rest of this paper is organised as follows. Section II briefly reviews some brain inspired models that are related to the three key characteristics of human brain. Section III presents our proposed brain inspired model - Hierarchy and Granularity based Multimodal (HGM) Conceptual Model with some definitions, architectures and discussion in relation to finding multi-view patterns. This is followed by the discussion of a structurally adaptive neural networks, as an implementation approach of the proposed conceptual model. Section V demonstrates the functionalities of the proposed model with a simple data set and discusses the experimental results. Section VI concludes this paper.

II. Review of Related Works

The study of machine intelligence has recently made a paradigm shift towards brain inspired computing approach. This has led to the quest on investigating and understanding the biological structure and functionalities of human brain. Subsequently, such investigations and understanding could be very useful for the design and development of a brain inspired machine or computer systems that could be further applied in many fields. Therefore, there are many artificial architectures or systems that are involved in the pursue of this goal. Specifically, we focus our discussion on research endeavours that are more related and relevant to the state of hierarchy, granularity and multimodality in human brain. Hence, we focus on two main models or frameworks as below:

- the Audio Visual Information Processing (AVIS) and its implementation in Person Identification based on Auditory and Visual Information (PIAVI).
- the Memory-Prediction Framework and its implementation in Hierarchical Temporal Memory.

AVIS [11] is a connectionist framework that integrates multimodal inputs (i.e. visual and audio inputs). Such two modes of inputs are processed at different levels of granularity. For different levels in visual subsystem and auditory subsystem (i.e. V1 to V5 and A1 to A5), there exist different functions and characteristics to process inputs reciprocally. The raw inputs from two modes are processed at primitive levels and aggregation occurs at different levels of the auditory and visual subsystems. Eventually the higher levels of information are integrated at the higher-level concept subsystem.

In addition, the modes of operation for AVIS could be unimodal, bimodal and cross-modal. Unimodal processing refers to individual processing of auditory and visual subsystems while bimodal processing implies that visual subsystem could process visual inputs as well as audio inputs and vice versa for auditory subsystem. On the contrary, cross-modal processing operates by having visual subsystem to process auditory inputs only and vice versa. AVIS has been applied and implemented as PIAVI in [11]–[13] with promising experimental results. In addition, it has been reported that multimodal processing of visual and audio inputs is able to outperform single mode processing.

On the other hand, [14] has proposed Memory-Prediction Framework as a theory that is inspired from biological perspective, particularly from his studies on neocortex. According to [14], bottom-up processing of inputs from human sensors are hierarchically processed and abstracted from primitive level and into higher level where much more meaningful information is extracted and emerged. Therefore, as the abstraction move upwards, the information is getting more invariant and such high level information is used for future prediction of future new inputs. Relatively, future prediction occurs with a top-down process where invariant information being matched with bottom-up new inputs. The prediction involves matching of partial sequences and expectations at higher level are projected to the lower level inputs with reciprocal propagation of information.

Hence, the invariant information at high level of abstraction is more stable temporally in comparison to the lower level where sensory data is raw, novel and thus always changes temporally. [14] also applies Memory-Prediction Framework to explain the association for integrating different senses such as visual, audio and touch. The implementation and formalisation of Memory-Prediction Framework has been discussed in [15] and a technological product named Hierarchical Temporal Memory (HTM) is produced. HTM replicates the structural and algorithmic properties of neocortex and bears some resemblance to machine learning technique such as Bayesian Networks [15].

Apparently, AVIS and Memory-Prediction Framework have illustrated the three key characteristics of human brain. Therefore, it is important that these characteristics, namely Hierarchy, Granularity and Multimodality could be portrayed in a brain inspired conceptual model. Particularly, we believe that the hybrid of these characteristics is useful and significant for identifying patterns in the field of Data Mining.

III. The Hierarchy and Granularity based Multimodal (HGM) Conceptual Model

Based on the study of biological properties of human brain and the review of related research works, a brain inspired framework is proposed, namely the Hierarchy and Granularity based Multimodal (HGM) Conceptual Model. The definitions of the key characteristics of the model is firstly specified prior to the discussion of the architecture of HGM. Subsequently, the identification of multi-view patterns with HGM is presented.

A. The Definitions of Hierarchy, Granularity and Multimodality

The definitions of Hierarchy, Granularity and Modality are presented individually. Subsequently, the definitions that link these characteristics in the state of multimodality are also presented. These definitions provide the foundations for further understanding and discussion of the HGM architecture and the experimental results.

1) Definitions of Modality:

- A modality is a domain-related or context-related data source. Thus, given a specific domain, domain experts is normally required to manually group or select relevant attributes in accordance to modality.
- A modality m consists of a collection of relevant features $f_i \in F$, where F is a finite set of feature space and $i = \{1, 2, \ldots, n\}$. For example, the relevant features for the modality of patients in the domain of medical could be age, address, contact numbers, etc.

2) Definitions of Hierarchy:

- The definitions about hierarchy focus on how different types of concept hierarchy could be formed for a given modality m. Therefore this section will formally discuss how different features f_i could contribute to the formation of feature-related concept hierarchies.
- Within a modality m, features f_i where $i = 1, 2, \ldots n$, could be selected from feature space F to form feature subspace $F_d^* \subset F$ where $d = 1, 2, \ldots n$.
- Given a modality m, the element of empty set, $\emptyset$ or $\binom{n}{0}$ is always discarded. This is because at least a feature f_i is required for a feature subspace F_d^*. In fact, the element of $\{f_1, f_2, f_3\}$ is not included in F_d^* because $F_d^* \subset F$ where $r = 1, 2, \ldots n$ and it should be included in F. Eventually, we assume that the maximum feature subspaces F_d^* that could be produced for a modality m is $2^n - 2$. Subsequently, the combinatorial identity for a modality m would be:
$$\binom{n}{1} + \binom{n}{2} + \ldots + \binom{n}{n-1} = 2^n - 2, \text{ for } n \geq 0.$$
- The feature subspaces F_d^* and feature space F in a modality m could be mapped accordingly to a numbers of different concept hierarchies ch_h where $h = 1, 2, \ldots, n$. Let CH_m denote the set of concept hierarchies formed in a modality m, also termed Modality Hierarchy Space, where $ch_h \in CH_m$.

3) Definitions of Granularity:

- A Concept Hierarchy $ch_h \in CH_m | h = \{1, 2, \ldots, q\}$ is a kind of partially ordered set (poset) where ch_h is a finite set of concepts and $\prec$ is a partial order on ch_h.
- Let x, y, z denote the concepts. y is called a nearest ancestor of x, if the following conditions are satisfied:
  1) $x, y \in ch_h$ with $x \prec y$ and $x \neq y$
  2) There is no $z \in ch_h$ such that $x \prec z$ and $y \prec z$
- If there is a maximum element in ch_h and a set of $ch_{h,l}$ where $h = 1, 2, \ldots, q$ and $l = 1, 2, \ldots, r$, such that
$$ch_h = \bigcup_{l=1}^{n} ch_{h,l} \text{ and } ch_{h,i} \cap ch_{h,j} = \emptyset \text{ for } i \neq j$$
In addition, if a nearest ancestor of a concept in $ch_{h,i}$ is in $ch_{h,j}$, then the nearest ancestor of the other concepts in $ch_{h,i}$ are all in $ch_{h,j}$.
- Within a modality m, the level number l for a concept hierarchy is regarded as the levels of granularity $l \in L$ for a concept hierarchy ch_h where L is a finite set and $l = 1, 2, \ldots, r$.
- Similarly, the concepts could be regarded as the granule $g \in G$ for each level l where G is a finite set and $g = 1, 2, \ldots, s$ in a given modality m.

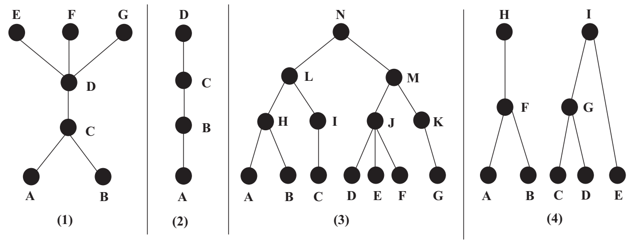

Fig. 1. Some examples of concept hierarchy [16].

- For instance, with regards to sample 3 in Figure 1, the greatest or the maximum granule or concept is N and it could be termed $ch_{3,1,1}$. It means that N is at 3rd hierarchy with 1st granule at 1st level. Similarly, from the same sample, $ch_{3,3,4}$ is referred to K. In addition to sample 3, $\{ch_{3,4,1}, ch_{3,4,2}\} \subset ch_{3,3,1} \rightarrow \{A, B\} \subset D$ shows the abstraction of granules.
- If we are to consider all the examples of concept hierarchies in Figure 1 as belongs to modality m_1. Thus, in general, we could add another dimension to label a concept hierarchy as $ch_{m,h,l,g}$. With regards to sample 3, we could then label N as $ch_{1,3,1,1}$, which means N is in modality m_1, at 3rd hierarchy with 1st granule at 1st level. This additional information of modality m is very important as it allows patterns to be identified across multimodality.

4) Definitions of Multimodality:

- Let V_θ denote the state or environment of multimodality. A collection of different types of modality m_i , where V_θ is a finite set with $V_\theta = \{m_1, m_2, \ldots, m_n\}$.
- The pair of concepts $ch_{m,h,l,g}$ where $h = 1, 2, \ldots, q$, $l = 1, 2, \ldots, r$ and $g = 1, 2, \ldots, s$, could be associated via a mapping function such that
$$T : CH_i \rightarrow CH_j \text{ for } i \neq j$$
- This means that each concepts in the concept hierachies of the Concept Hierarchy Space CH_m for each modality m_i are mapped in pairs.

B. *The Architecture of HGM*

The proposed conceptual framework was inspired by the multimodal information processing from [12]. Particularly, HGM has been modified to accommodate the three key characteristics - Hierarchy, Granularity and Multimodality, that are formally defined previously. The design of HGM has been tailored to cope with more modalities and hierarchies of data that could appear at multiple levels of granularity. Thus it is comparatively more flexible and allows large amount of data explorations.

The flow of data inputs in HGM is depictd in Figure 2. Apparently, all modalities of data inputs are pre-processed and fed into HGM from the top and bottom separately. In particular, data inputs from the bottom are separated into different types of modality. Specifically, such separation is conducted by humans with their knowledge of a particular domain. Within HGM, two pattern identification approaches are deployed, namely Global Pattern Identification (GPI) and Local Pattern

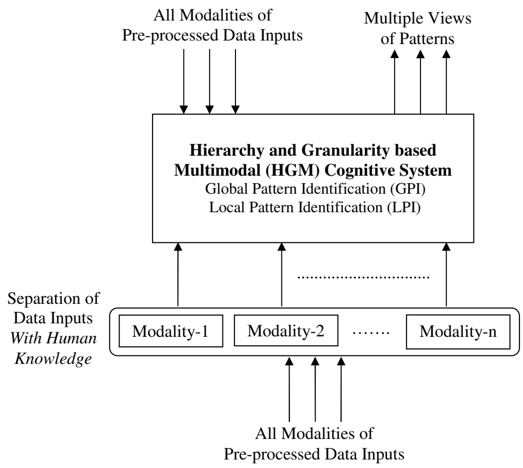

Fig. 2. The top-down and bottom-up flow of data in HGM

Identification (LPI). The outputs of HGM consists of global and local patterns. In fact, the outputs of HGM have been generalised or abstracted from data to information(patterns) that are presented in different views. Therefore, HGM facilitates extensive and intensive data explorations and multiple views of patterns could be obtained.

The architechture of HGM is illustrated in Figure 3. It is noticeable that HGM is designed as a three dimensional architecture to accommodate the presentation of patterns from different views or perspectives. We believe that patterns are deemed to appear in different types of concept hierarchy ch and at different levels of granularity as well as across different types of modality. To generate and identify multimodal patterns with different hierarchies and granularities, HGM subsequently explores and identifies patterns in the following four perspectives:

- Vertical View
- Depth View
- Horizontal View
- Global View

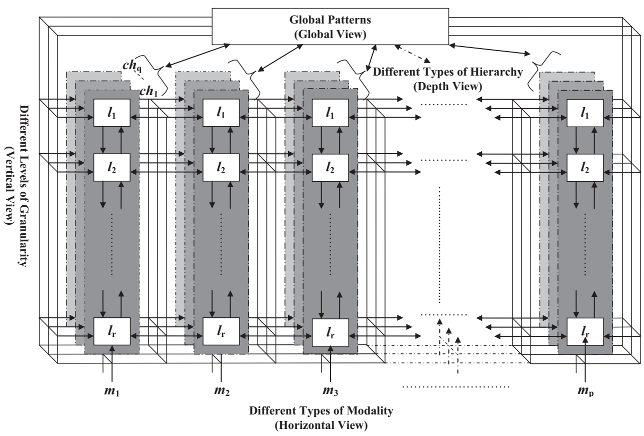

Fig. 3. The architechture of HGM

With regards to the two pattern identification approaches, Local Pattern Identification (LPI) consists of the first three perspectives. In particular, Vertical View presents patterns at different levels of granularity for different types of concept hierarchies which are obtained from Depth View. Furthermore, Depth View and Vertical Views could facilitate unimodal pattern analysis and therefore pattern exploration is restricted to features relevant to a particular modality. Subsequently, the pattern exploration in Horizontal View spans across unimodality that comprises of different levels of granularity and different types of hierarchy.

To further illustrate the three perspectives, Local Pattern Identification (LPI) could be graphically illustrated in Figure 4. The different types of modality are represented in different shapes while the different types of concept hierarchy are represented in different colors. Regardless of unimodality or multimodality, different levels of granularity could be observed. Therefore, the granules that comprise for each level of a hierarchy shows different abstractions in patterns.

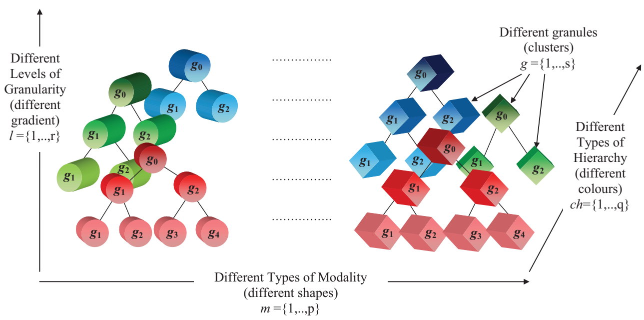

Fig. 4. The representation of the three views in Local Pattern Identification (LPI) with gradient, colours and shapes

On the contrary, the fourth perspective - Global View, is referred to Global Pattern Identification(GPI). Specifically, patterns are represented in Global Concept Hierarchy in order to obtain a global and brief idea of patterns. Such approach is rather similar to traditional way of exploring data from an integrated database.

C. The Multiple Views in the Pattern Identification with HGM

HGM allows unimodal data to be explored by drilling down into different levels of granularity. Henceforth, Vertical View in HGM allows unimodal patterns at each level to be represented in a concept hierarchy. It is important to have patterns represented in a concept hierarchy as it provides different abstractions of the patterns which are represented in numbers of granules that constitute each levels of the hierarchy. Similarly, such characteristic demonstrates the flexibility of HGM to traverse vertically from high abstractions of patterns into lower abstractions of patterns in a unimodal data.

In addition, patterns could also be identified when different types of concept hierarchy is portrayed in Depth View. In other words, this means that different types concept hierarchy could be generated with regards to the numbers of relevant attributes or features that exist in a particular modality. Given the same set of features or attributes, each feature in that particular modality could subsequently produce different views of patterns identified. Similarly, such concept hierarchies could also be examined at different levels of granularity. In fact, patterns that appear in different types of concept hierarchies could be cross correlated. For instance, patterns that appear in first hierarchy ch_1 at first level l_1 could be linked and cross correlated with patterns appear in last hierarchy ch_q at first level l_1. Therefore, patterns could be viewed differently within a unimodality.

Data from an application domain are differentiated and separated into multimodalities, as represented as Modality m in Figure 3. Thus, Horizontal View could obtain multimodal patterns in distributed and parallel manner. In addition, the identification of patterns in unimodality could be examined by linking the unimodal patterns with other patterns that exist in other different modalities. This is depicted in Figure 3 where multiple modalities of data are interconnected to each others at different levels of granularity. For instance, patterns that appear in first modality m_1 at first level l_1 could be linked and cross correlated with patterns appear in third modality m_3 at second level l_2. Therefore, the flexibility of HGM facilitates the thorough examinations of data.

Although patterns could also be revealed and represented in Global Concept Hierarchy, the levels of granularity would be limited. This is because all modalities of data are represented in a single hierarchy and therefore patterns identified tend to be portraying high level of coarseness. In other words, patterns identified in unimodality or multimodality, specifically portraying Vertical View, Depth View and Horizontal View, could have lower coarseness. Nonetheless, Global Pattern Identification (GPI) is still capable of portraying Global View of a domain. Patterns represented in Global Pattern Identification (GPI) could be useful. In fact, the holistic view of a domain could provide preliminary guidance to the in depth exploration for discovering hidden and unexplored patterns in Local Pattern Identification (LPI).

IV. The GSOM

Various techniques such as clustering, classification, association rules, decision trees, and the combinations of them could be deployed to implement HGM. Nevertheless, we are particularly interested in representing patterns in clusters as data inputs could be grouped naturally without explicit advice from domain experts. Thus, we present an existing and plausible technique, namely Growing Self Organising Maps (GSOM), with some justifications.

A. The GSOM Algorithm

An extension of the SOM, called the Growing Self Organizing Maps (GSOM) has been developed with the capability of self adapting according to the input data and could better represent clusters [17], [18].

Unlike SOM, Growing Self Organizing Maps does not start with a predefined network, instead it is initialised with four nodes as shown in Figure 5. The four nodes are named as the boundary nodes. The entire node generation process begins at the boundary nodes in which each of the nodes are allowed to grow freely into desired directions. Figure 6 shows the process of node generation from boundary nodes. The new node is grown to represent input data using a heuristic approach and the allocation of weight values of nodes during node growth are similar to SOM, which is self organised.

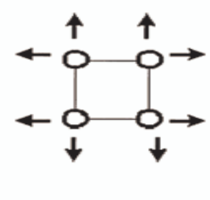

Fig. 5. The initial GSOM [18]

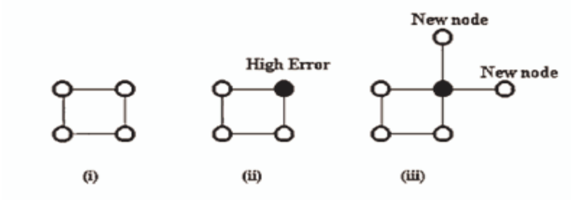

Fig. 6. New node generation from the boundary of the network [18]

To control the spread of the map, a concept called Spread Factor (SF) is developed for specifying the amount of spread that is needed for the analysis on data. Such characteristic allows clustering to be done hierarchically by gradually adjusting the values in Spread Factor. In fact, Spread Factor takes values from 0 to 1 and is regardless to the dimensions in the data. Therefore, data analysis usually begins with low value and slowly increases the further observations of the selected region of data. Thus, it allows comparison of results in multiple abstractions on the same data sets and also the comparison of results of different data sets with a different number of attributes by mapping them with the same Spread Factor.

The following shows GSOM process, further explanations is described in [18].

1) Initialization phase:
   a) Initialize the weight vectors of the starting nodes (usually four) with random numbers between 0 and 1.
   b) Calculate the growth threshold(*GT*) for the given data set of dimension *D* according to the spread factor(*SF*) using the formula:

$$GT = D \times ln(SF)$$

2) Growing Phase:
   a) Present input to the network.
   b) Determine the weight vector that is closest to the input vector mapped to the current feature map (winner), using Euclidean distance. This step can be summarized as: find *q'* such that

$$|\vartheta - \omega_{q'}| \leq |\vartheta - \omega_q| \;\; \forall q \in \mathbf{N}$$

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where ϑ, ω are the input and weight vectors respectively, q is the position vector for nodes and $\mathbf{N}$ is the set of natural numbers.

c) The weight vector adaptation is applied only to the neighbourhood of the winner and the winner itself. The neighbourhood is a set of neurons around the winner, but in the GSOM the starting neighbourhood selected for weight adaptation is smaller compared to the GSOM (localized weight adaptation). The amount of adaptation (learning rate) is also reduced exponentially over the iterations. Even within the neighbourhood, weights that are closer to the winner are adapted more than those further away. The weight adaptation can be described by

$$\omega_j(k{+}1) = \begin{cases} \omega_j(k) \\ if\ j \neq \mathbf{N}_{k+1} \\ \omega_j(k) + LR(k) \times (x_k - \omega_j(k)) \\ if\ j \in \mathbf{N}_{k+1} \end{cases}$$

where the Learning Rate $LR(k)$, $k \in \mathbf{N}$ is a sequence of positive parameters converging to zero as $k \rightarrow \infty$. $\omega_j(k)$ and $\omega_j(k{+}1)$ are the weight vectors of the node j before and after the adaptation and $\mathbf{N}_{k+1}$ is the neighbourhood of the winning neuron at the $(k{+}1)$th iteration. The decreasing value of $LR(k)$ in the GSOM depends on the number of nodes existing in the map at time k.

d) Increase the error value of the winner (error value is the difference between the input vector and the weight vectors).

e) When $TE_i \geq GT$ where TE_i is the total error of node i and GT is the growth threshold. Grow nodes if i is a boundary node. Distribute weights to neighbours if i is a non-boundary node.

f) Initialize the new node weight vectors to match the neighbouring node weights.

g) Initialize the Learning Rate LR to its starting value.

h) Repeat steps (b) – (g) until all inputs have been presented and node growth is reduced to a minimum level.

3) Smoothing phase:

   a) Reduce learning rate and fix a small starting neighbourhood.

   b) Find winner and adapt the weights of the winner and neighbours in the same way as in growing phase.

B. Justifications of Using GSOM for Implementation of HGM

Given a variety of clustering techniques, we have chosen GSOM as the implementation techniques over the other clustering techniques. The justifications or reasons of using GSOM to implement HGM are listed below:

1) The characteristics of flexible and adaptive are shown in the growing nature of GSOM. Thus it is a plausible technique to mimic the evolving nature of human brain.
2) It allows hierarchical clustering to be conducted via the control of Spread Factor (SF). This characteristic is very important in concept hierarchy generation in HGM in which different levels of granularity is necessary to form the hierarchy. In fact, it again shows the plausible way to mimic the biological structure of human brain in terms of the nature of information processing in terms of a hierarchy.
3) It is a good visualisation tool to observe patterns on a two-dimensional map. In fact, different granules (clusters) are visualised in different maps. Thus, this aid in analysis when multiple maps are generated and compared within unimodality or multimodality.

V. Experimental Results

A simple benchmark dataset from UCI Machine Learning Repository is used as a case study to look at some possible patterns that could be identified by HGM. In fact, the case study is meant to demonstrate the properties of HGM, especially in identifying patterns from the four different perspectives.For the purpose of this case study, the Zoo Data Set donated by [19] is selected due to its completeness (no missing data), simplicity in the use of simple and less technical descriptions of the features or attributes and multivariate characteristics.

The multimodality of Zoo Data Set is first identified with human knowledge. Subsequently, the multi-view of patterns are identified with GSOM based implementation structure of HGM Cognitive System.

A. The Multimodality in Zoo Data Set

The Zoo Data Set contains 17 attributes or features and classes with 101 instances or feature vectors. These features include animal name, hair, feathers, eggs, milk, airborne, aquatic, predator, toothed, backbone, breathes, venomous, fins, legs, tail, domestic, catsize. In fact, animal name is considered as the ID of the feature vectors. The classes for each feature vectors are not included during the clustering processes. However, classes are useful during the clusters (granules) analysis. Thus, only 16 attributes or features are used to identify patterns in Global View.

As discussed previously, multimodality refers to the context related data sources in a domain. Therefore, the 15 attributes or features in Zoo Data Set could be separated manually with human knowledge into several different modalities. Specifically, the multimodality of data sources is obtained by asking and answering the following questions:

1) What does the animal physically has on its body? This refers to the physical features or body parts of an animal.
2) How does the animal function? This refer to the habits of an animal.
3) Where does the animal live? This refer to the habitats of an animal
4) How dangerous is the animal? This refer to the threats that naturally imposed by an animal.

Thus, Table I shows the classifications of the attributes or features into four modalities.

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TABLE I
THE MULTIMODALITY IN ZOO DATA SET

Modality m	**Related Features** $f_i \in F$
Modality-1, m_1:Physical Features (Body Parts)	$F_{m_1} = \{f_1, f_2, f_3, f_4, f_5, f_6, f_7\}$ $\rightarrow$ {hair, feathers, toothed, backbone, fins, legs, tail}
Modality-2, m_2:Habits	$F_{m_2} = \{f_8, f_9, f_{10}\}$ $\rightarrow$ {eggs, milks, breathes}
Modality-3, m_3:Habitats	$F_{m_3} = \{f_{11}, f_{12}\}$ $\rightarrow$ {airborne, aquatic}
Modality-4, m_4:Threats	$F_{m_4} = \{f_{13}, f_{14}, f_{15}, f_{16}\}$ $\rightarrow$ {predator, venomous, domestic, catsize}

TABLE III
THE TYPES OF CONCEPT HIERARCHIES FOR THE MODALITY OF HABITAT

Hierarchy $ch_h \in CH_m$	**Related Features** $f_i \in F$ **or** $f_i \in F_d^*$
ch_1	$F =$ {aquatic, airborne}
ch_2	$F_1^* =$ {aquatic}
ch_3	$F_2^* =$ {airborne}

B. The Multi-View of Patterns

Given the multimodality of Zoo Data Set, some experimental results are presented according to the GSOM based implementation strategy. These results tend to demonstrate how HGM functions as model in identifying multi-view patterns. Thus, only reasonable amounts of simple patterns are analysed and discussed. The comprehensive and complete association of all concepts are not presented and discussed since the processes are repetitive.

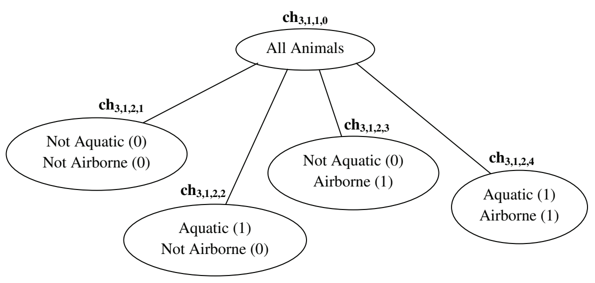


Fig. 8. One of the concept hierarchies for the modality of habitat, ch_1 with $F =$ {aquatic, airborne}

The Global Patterns in Global View is firstly identified with highest Spread Factor (SF = 0.9). The visualisation of Global View is depicted in Figure 7 with the clusters (granules), g_i where $i = 1, \ldots, 5$, visually identified and labelled. It is noticeable that how different classes are distributed in different clusters. The cluster characteristics and interpretations are presented in Table II.

Subsequently, the concept hierarchies of m_3 is constructed. As there are two features or attributes for m_3, the feature subspaces F_d^* required is would be $d = 2^n - 2$ where $n = 2$. Thus, that means that we have we could construct concept hierarchies with features as listed in Table III.

The concept hierarchy for ch_1 in which all the features for modality of Habitat are depicted in Figure 8. It is noticeable that each of concepts are labelled in terms of levels of granularity, types of concept hierarchies and types of modalities. Likewise, the feature subsets F_1^* and F_2^* produce ch_2 and ch_3 respectively and they are displayed in Figure 10.

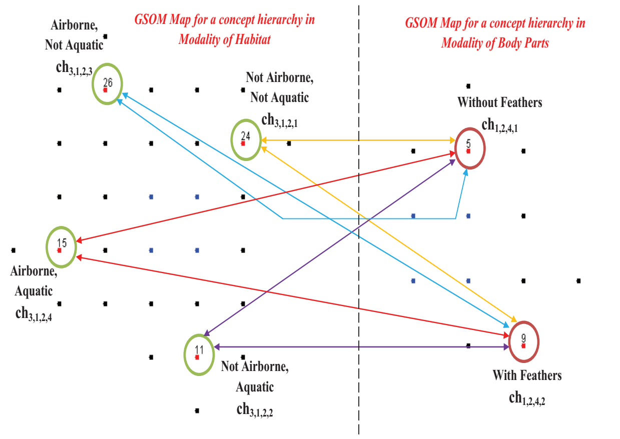


Fig. 9. The concepts associations between the modality of habitat and the modality of body parts (feathers) for Horizontal View.

With the concept hierarchies cosntructed for the m_3, we could proceed with identification of multi-view patterns. As mentioned previously, only sufficient experimental results are discussed to show the functionality of finding multi-view patterns with HGM. Therefore, experiments are designed to be conducted as below for finding multi-view patterns:

1) Association of concepts between $ch_{3,1,2,g}$ where $g = 1, \ldots, 4$ with $ch_{3,1,1,0}$ to show the patterns identified at Vertical View in LPI.
2) Association of concepts between $ch_{3,1,2,g}$ where $g = 1, \ldots, 4$ with $ch_{3,2,2,g}$ where $g = 1, 2$ to show the patterns identified at Depth View in LPI.
3) Association of concepts between $ch_{3,1,2,g}$ where $g = 1, \ldots, 4$ with $ch_{1,2,4,g}$ where $g = 1, 2$ to show the pattern identification in Horizontal View. In this case, we assume the concept hierarchy of type of is actually representing the feature-feathers.
4) Association of concepts between $ch_{3,1,2,1}$ where with g_i where $i = 1, \ldots, 5$ of Global Patterns, to show the association between between concepts in any concept hierarchies in LPI with Global Patterns in GPI.

In the case of association of concepts between $ch_{3,1,2,g}$ where $g = 1, \ldots, 4$ with $ch_{3,1,1,0}$, $ch_{3,1,1,0} = \bigcup_{g=1}^{4} ch_{3,2,1,g}$ and $ch_{3,2,1,1} \cap ch_{3,2,1,2} \cap ch_{3,2,1,3} \cap ch_{3,2,1,4} = \emptyset$. Thus, it is not necessary to show cluster occurence matrix for this scenario is not shown as the traversal of concepts in ch_1 in m_3 is very limited, which is just two levels.

Similarly, $ch_{3,2,2,g}$, where $g = 1, 2$, is subsets of $ch_{3,1,2,g}$ where $g = 1, \ldots, 4$. Therefore the cluster occurence matrix will be 100% for pattern identifications in Depth View. Thus, the cluster occurence matrix for such scenario is not necessary.

Although the different concept hierarchies are using feature subsets and showing very similar groupings within a modality, they are still useful in showing different groupings of animals in comparison to the Global Patterns in Global View as well as groupings in another modality. This means that, animals are grouped into two groups with the feature of Aquatic will have

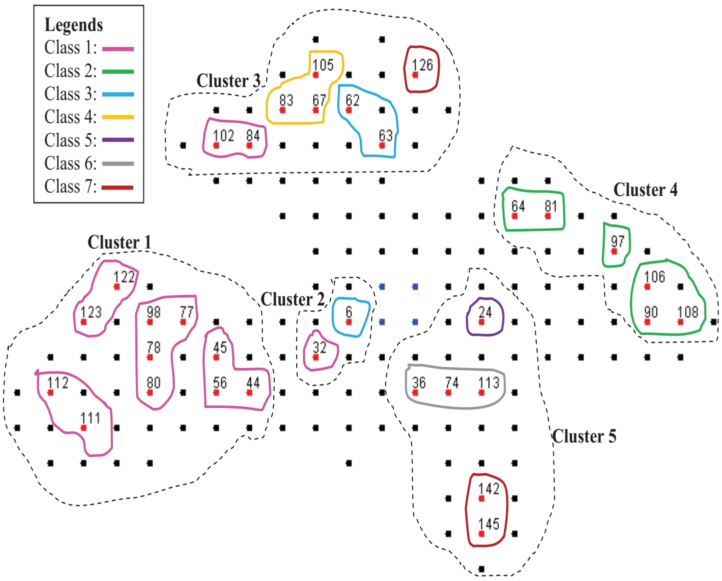
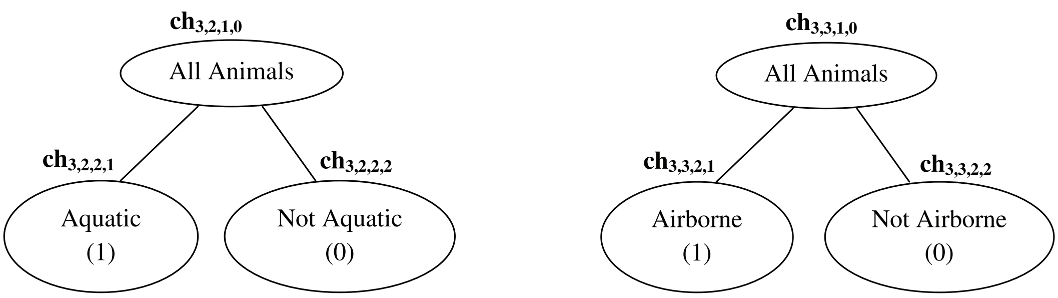


Fig. 7. A GSOM visualisation for Global View

TABLE II
THE CLUSTER CHARACTERISTICS OF ZOO DATA SET IN GLOBAL VIEW

Clusters (Granules) $g_i \in G$	**Cluster Characteristics and Interpretation**
Cluster 1, g_1	Consists of animals from Class 1, which are actually mammals. Examples of animals include: bear(node 77), pussycat(node 98), fruitbat(node 111), sealion(112), gorilla(node 123), girl or human(node 122), mole (node 45) and hamster (node 56).
Cluster 2, g_2	Consists of animals from Class 1 and 3. There are only two animals: platypus(node 32) and tortoise(node 6). They both lay eggs have 4 legs. However, playtypus is clustered closer to g_1 as it also shows features of a mammal.
Cluster 3, g_3	Consists of animals from Class 1, 3, 4 and 7. Examples of animals include: seal(node 102), dolphin(node 84), tuna(node 83), bass(node 67), seahorse(node 105), seasnake(node 62), slowworm(node 63) and seawasp(node 126). They are all aquatic animals except slowworm.
Cluster 4, g_4	Consists of animals from Class 2, which are actually birds. Examples of animals include: penguin(node 64), crow(node 81), ostrich(node 97), chicken(node 108), duck(node 90) and flamingo(node106).
Cluster 5, g_5	Consists of animals from Class 4, 5, 6 and 7. Examples of animals include: frog(node 24), honeybee(node 36), star fish(node 74), crab(node 113), worm(node 142) and clam(node145). All these animals do not have backbone except frog(node24).



(a) ch_2 with $F_1^*\{\text{aquatic}\}$ (b) ch_3 with $F_2^*\{\text{airborne}\}$

Fig. 10. The other two concept hierarchies for the modality of habitat

different groupings, say with feature of predator. As such, we regard that patterns are actually identified and viewed from different angles.

To portray the patterns identified in Horizontal View, $ch_{1,2,4,g}$ where $g = 1, 2$ represent the 4th concept hierarchy in the modality of physical features or body parts, m_1. In fact, Figure 9 graphically shows the association between concepts (clusters) when two GSOM maps are laid side by side. It could be seen from Figure 9 that feature vectors or instances are clustered differently with different subsets of features. Subsequently, we could identify the cluster occurence matrix for patterns identified at Horizontal View in Table IV.

According to the two tables, we could brifely summarise that if an animal has feathers, they are birds that could live on three kinds of habitats, namely in the water, air, and ground.

Based on the Cluster Occurence Matrix for Habitat-Feathers, we further interprete the clusters (granules) and some simple rules that describes the characteristics of the clusters (granules) could be extracted. Therefore, patterns which are identified in Horizontal View could be summarised in Table V and Table VI.

In addition to Horizontal View, the concepts ch_1 in the modality of habitat, m_3 could be associated with the clusters g_i in Global View. The cluster occurence matrix for such association is given in Table VII. From the table, it is noticeable that there are few cluster occurrences that are higher than 50%. Basically, these clusters could validate the global patterns although with only partially identified local patterns.

VI. Conclusion

This paper presents a novel brain inspired conceptual model named HGM for identification of multi-view patterns. An implementation approach of using GSOM for representing patterns in hierarchical structures is discussed. To demonstrate the functionalities of HGM, some experimental results of a simple case study with bench mark data set is presented and discussed. Although the experimental results are not comprehensive, it is sufficient enough to show the feasibility of identifying multi-view patterns with HGM.

The proposal of HGM has opened up several potential future research works. For instance, it is necessary to consider the computational complexity and scalability of HGM with real data sets. In addition, the implementation of the conceptual model could be extended and enhanced with incremental learning capability and associative memory approach.

References

[1] C. B. Saper, S. Iversen, and R. Frackowiak, "Integration of sensory and motor function: The association areas of the cerebral cortex and the cognitive capabilities of the brain," in *Principles of neural science*, 4th ed., E. R. Kandel, J. H. Schwartz, and T. M. Jessell, Eds. New York: McGraw-Hill, 2000, ch. 19, pp. 349–380.

[2] V. Mountcastle, "The columnar organization of the neocortex." *Brain*, no. 120, pp. pp. 701–722, 1997.

[3] K. Friston, "Hierarchical models in the brain," *PLoS Computational Biology*, vol. 4, no. 11, 2008.

[4] D. L. Hall and J. Llinas, "An introduction to multisensor data fusion," *Proceedings of the IEEE*, vol. 85, no. 1, pp. pp. 6–23, 1997.

[5] J. R. Hobbs, "Granularity," in *Proceedings of the 9th International Joint Conference on Artificial Intelligence (IJCAI)*. Los Angeles, USA: Morgan Kaufmann, 1985, pp. 432–435.

[6] Y. Yao, "Perspectives of granular computing," in *IEEE International Conference on Granular Computing (GrC)*, Beijing, China, 2005, pp. 85–90.

[7] Y. Chen and Y. Yao, "A multiview approach for intelligent data analysis based on data operators," *International Journal of Information Sciences*, vol. 178, pp. pp. 1–20, 2008.

[8] ——, "Multiview intelligent data analysis based on granular computing," in *IEEE International Conference on Granular Computing (GrC)*, Atlanta, USA, 2006, pp. 281–286.

[9] M. Minsky, *The Emotion Machine : commensense thinking, artificial intelligence, and the future of the human mind*. New York: Simon & Schuster, 2006.

[10] S. Zhang, C. Zhang, and X. Wu, *Knowledge Discovery in Multiple Databases*. London, UK: Springer-Verlag, 2004.

[11] N. Kasabov, E. Postma, and J. van den Herik, "Avis: a connectionist-based framework for integrated auditory and visual information processing," *Information Sciences*, vol. 123, pp. pp. 127–148, 2000.

[12] N. Kasabov, "Evolving systems for integrated multi-modal information processing," in *Evolving Connectionist Systems: Methods and Applications in Bioinformatics, Brain Study and Intelligent Machine.* London: Springer-Verlag, 2003, ch. 13, pp. 257–271.

[13] ——, "Evolving intelligent systems for adaptive multimodal information processing," in *Evolving Connectionist Systems The Knowledge Engineering Approach*. London: Springer-Verlag, 2007, ch. 13, pp. 361–380.

[14] J. Hawkins and S. Blakeslee, *On Intelligence*. New York: Times Books, 2004.

[15] J. Hawkins and D. George, "Hierarchical temporal memory - concepts, theory, and terminology," Numenta Inc., Redwood City, California, White Paper, 2007.

[16] Y. Lu, "Concept hierarchy in data mining: Specification,generation and implementation," Master's thesis, Simon Fraser University, Canada, 1997.

[17] D. Alahakoon, S. K. Halgamuge, and B. Srinivasan, "A self growing cluster development approach to data mining," in *IEEE Conference Systems, Man and Cybernetics*, San Diego, USA, 1998, pp. 2901–2906.

[18] ——, "Dynamic self-organizing maps with controlled growth for knowledge discovery," *IEEE Transactions on Neural Networks*, vol. 11, no. 3, pp. pp. 601–614, 2000.

[19] R. S. Forsyth, "Uci machine learning repository, zoo data set," 1990. [Online]. Available: http://archive.ics.uci.edu/ml/datasets/Zoo

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TABLE IV
THE CLUSTER OCCURENCE MATRIX FOR THE MODALITY OF HABITAT AND THE MODALITY OF BODY PARTS (FEATHERS). TFV REPRESENTS THE TOTAL NUMBERS OF FEATURE VECTORS AND CO REPRESENTS THE CLUSTERS (GRANULES) OCCURENCE IN PERCENTAGE.

	$ch_{1,2,4,1}$			$ch_{1,2,4,2}$		
	$TFV_{ch_{3,1,2,g}}$	$TFV_{ch_{1,2,4,g}}$	CO(%)	$TFV_{ch_{3,1,2,g}}$	$TFV_{ch_{1,2,4,g}}$	CO(%)
$ch_{3,1,2,1}$	43	46	93.48	3	46	6.52
$ch_{3,1,2,2}$	30	31	96.77	1	31	3.23
$ch_{3,1,2,3}$	8	19	42.11	11	19	57.89
$ch_{3,1,2,4}$	0	5	0.0	5	5	100.00

TABLE V
THE CLUSTER INTERPRETATIONS AND CHARACTERISTICS RULES FOR THE MODALITY OF HABITAT AND THE MODALITY OF BODY PARTS (WITHOUT FEATHERS)

Habitats	Without Feathers,$ch_{1,2,4,1}$	Characteristic Rules
Not Airborne, Not Aquatic, $ch_{3,1,2,1}$	Majority of the animals are from Class 1 (mammals). Some are from Class 3, 6, 7, which includes flea, scorpion, termite, tortoise, worm.	IF Habitat is Not Airborne $\bigwedge$ Not Aquatic $\bigwedge$ Without Feathers THEN Animal is either Mammals or Creature Without Backbone living on the ground.
Not Airborne, Aquatic, $ch_{3,1,2,2}$	Majority of animal are from class 4 (fish). Some aquatic creatures without backbone such as octopus, crab, crayfish, lobster, starfish, seasnake and special mammals such as dolphin, sealion, playtypus, mink are also grouped into this cluster.	IF Habitat is Not Airborne $\bigwedge$ Aquatic $\bigwedge$ Without Feathers THEN Animal could be Fish or Special Types of Mammals (platypus) or Aquatic Creatures Without Backbone
Airborne, Not Aquatic, $ch_{3,1,2,3}$	Majority of animal (6 out of 8) are from class 6 (insects). The insects which are clustered into this group include honeybee, ladybird, housefly, month, wasp and gnat. There are two special mammals grouped into this cluster, namely fruitbat and vampire.	IF Habitat is Airborne $\bigwedge$ Not Aquatic $\bigwedge$ Without Feathers THEN Animal could be Insects or Special Types of Mammals (fruitbat).
Airborne, Aquatic, $ch_{3,1,2,4}$	No animal is clustered into this group.	IF Habitat is Airborne $\bigwedge$ Not Aquatic $\bigwedge$ Without Feathers THEN No Such Animal.

TABLE VI
THE CLUSTER INTERPRETATIONS AND CHARACTERISTICS RULES FOR THE MODALITY OF HABITAT AND THE MODALITY OF BODY PARTS (WITH FEATHERS)

Habitats	With Feathers,$ch_{1,2,4,2}$	Characteristic Rules
Not Airborne, Not Aquatic, $ch_{3,1,2,1}$	Consists of three animals from Class 2(birds):kiwi, ostrich and rhea	IF Habitat is Not Airborne $\bigwedge$ Not Aquatic $\bigwedge$ With Feathers THEN Specific Birds from Class 2 (ostrich)
Not Airborne, Aquatic, $ch_{3,1,2,2}$	Consists of one animal from Class 2(birds):penguin	IF Habitat is Not Airborne $\bigwedge$ Aquatic $\bigwedge$ With Feathers THEN Specific Birds from Class 2 (penguin)
Airborne, Not Aquatic, $ch_{3,1,2,3}$	Consists of animals from Class 2(birds):chicken, crow, dove, flamingo, hawk, lark, parakeet, pheasant, sparrow, vulture, wren.	IF Habitat is Airborne $\bigwedge$ Not Aquatic $\bigwedge$ With Feathers THEN Birds from Class 2 (crow)
Airborne, Aquatic, $ch_{3,1,2,4}$	Consists of five animals from Class 2(birds):duck, gull, skimmer, skua, swan.	IF Habitat is Airborne $\bigwedge$ Aquatic $\bigwedge$ With Feathers THEN Specific Birds from Class 2 (gull)

TABLE VII
THE CLUSTER OCCURENCE MATRIX FOR THE MODALITY OF HABITAT AND GLOBAL VIEW

	g_1		g_2		g_3		g_4		g_5	
$TFV_{ch_{3,1,2,g}}$	TFV_{g_1}	CO(%)	TFV_{g_2}	CO(%)	TFV_{g_3}	CO(%)	TFV_{g_4}	CO(%)	TFV_{g_5}	CO(%)
$TFV_{ch_{3,1,2,1}} = 46$	33	71.40	1	2.17	2	4.35	3	6.52	7	15.22
$TFV_{ch_{3,1,2,2}} = 31$	2	6.45	1	3.23	18	58.06	1	3.23	9	29.03
$TFV_{ch_{3,1,2,3}} = 19$	2	10.53	0	0.00	0	0.00	11	57.89	6	31.58
$TFV_{ch_{3,1,2,4}} = 5$	0	0.00	0	0.00	0	0.00	5	100.00	0	0.00