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Making Computer Learn Color

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***Abstract*—**Color categorization is shared among members in a society. This allows communication of color, especially when using natural language such as English. Hence sociable robot, to live coexist with human in human society, must also have the shared color categorization. To achieve this, many works have been done relying on modeling of human color perception and mathematical complexities. In contrast, in this work, the computer as brain of the robot learns color categorization through interaction with humans without much mathematical complexities.

***Keywords*—**Color categorization, color learning, machine learning.

I. Introduction

COLOR is an important element in visual world. It is widely used to represent something (e.g. using red to represent danger), as important cue to identify certain object, etc. Although color is physically the result of electromagnetic wave with different wavelength, human perceives color as categories, which may be indicated by name such as red, blue, etc. The color categorization is unique for each human being, due to the environment, task, and most importantly physical differences. Despite such individual differences, the categorization is shared among members in society to allow a successful communication. For example, the color category "red" must be shared in the society, hence when one uses the word "red", the other knows the color or the object with the color he refers to. This does not mean an absolute identical categorization, but sufficient to achieve a successful communication [1].

Sociable robot, which is aimed to live coexist with human in human society, must have not simply a color categorization, but color categorization shared in the society. Interestingly, human society is dynamics, in which color categorization may change and evolve in time. Currently the common approaches to achieve this, is by modeling human color perception or developing sophisticated clustering algorithm. In this work, a new approach is proposed. It focuses on enabling computer, as the brain of the robot, to learn categorization through interaction with human. By which the computer will arrive at shared color categorization with human.

The rest of this paper is organized as follows. Section 2 describes other research works to achieve color categorization by computer or artificial system. Section 3 describes the architecture and mechanism of color learning by interaction, whereas the result and discussion are presented in Section 4. And finally, Section 5 presents the conclusion of this work.

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II. Related Works

In general, research works to achieve color categorization by computer can be grouped into two approaches. The first approach is based on modeling and simulation of human color perception, whereas the other one focuses on developing new clustering algorithm for color categorization.

For computer to achieve not simply a color categorization, but color categorization as of human, modeling human color perception is certainly one possible and quite intuitive approach. In fact, many computer science and engineering solution has been found by modeling the nature. This approach may result in color categorization by computer as well as more understanding of human color perception itself.

Until now, there are still many unresolved issues in human color perception, including human color categorization. It is agreed that each human has its own unique color categorization which has no rigid boundary and cannot be described by mathematical formulation. However it is not yet understood how the categorization is shared among members in society. Moreover although the categorization may not be shared across society, high degree of similarity is found. There are three main hypotheses to understand human color categorization, i.e. nativism, empiricism and culturalism.

Based on nativism [2]-[5], the categorization is genetically determined and it is developed through evolution. During the lifetime, human only learns the names and activates these categories. Different culture and environment leads to different way and stage of genetic evolution. This explains why each society has shared color categorization, and how some degree of similarity can be found across different societies.

Based on empiricism [6][7], the categorization is the result of inductive learning solely from the environment. The genetic basis is only for the learning mechanism, whereas social interaction is only to learn the names of the already known shared categories. Living in the same environment results in the shared color categorization within a society.

Based on culturalism [8]-[10], the color categorization is the result of social interaction. Through feedback during social interaction, the color categorization is made and the color names are learnt. The social interaction is highly tied with the environment. The genetic basis is also necessary for the learning mechanism. As the members in society interact to each other, the color categorization is build and adapted between one and another, which will eventually stabilize as the shared color categorization.

Various models have been proposed to understand human color perception as well as to develop color categorization by computer or artificial system. Following nativism, Dowman [11] developed fuzzy Bayesian system to simulate color acquisition and the evolution of color categorization. Lammens [12] developed NPP color space based on neuro-physiological data. NPP color space aimed to relate visual stimuli (color as electromagnetic wave) and color categorization.

Steels and Belpaeme [1] develops various color categorization systems, modeling each of hypotheses to find out the best way of designing artificial system as well as to give comparison among them. For nativism, the color categorization is encoded into color genes and the genetic evolution is simulated. For empiricism, an inductive learning system using adaptive network is developed. For culturalism, they developed a few artificial systems to interact to each other.

Such modeling and simulation are in fact more towards to gain more understanding on human color perception, instead to develop the artificial one. It is because the model and simulation, in general, must also be concurred with other aspects of human such as: brain development, human's physiology and neurological processing, etc. which is not necessary for artificial system to follow.

Machine intelligence must be differentiated from computerized human intelligence [13]. In the same notion, artificial system does not necessary follow human color perception. The physical changes affecting color categorization, which may be in form of physical evolution between generations or brain development during the lifetime, etc., are not necessary to be implemented or modeled to develop artificial system. Human's brain and physical architecture which enables color perception including color categorization, are not necessary to be implemented in artificial system. As for example, it is not necessary for artificial system to have visual sensor the same as human's eye. The artificial system can be subset or superset of human color perception. The mechanism of human color perception may not be the best solution for artificial system, although it may still be inspired from human color perception.

On the other hand, the other approach focuses on developing new clustering algorithm for color categorization. They do not aim for color categorization shared with human, but for specific application such as image segmentation, object detection, etc. Artificial neural network (ANN) is generally used. Yin [14] uses RCE neural network for color categorization for hand segmentation, which can be extended for color based image segmentation in general. Yeo [15] uses combination between SOM and ART neural network. Other works, such as [16]-[18] also use ANN for color categorization.

ANN is commonly used mainly because of its learning capability, by which categorization need not be programmed. Through learning, the network adapts the input-to-category connection, so that when the input comes, the correct category can be invoked [19]. ANN is also in favor for modeling human color perception as it possesses hidden units between input and output, which can be interpreted as the internal representation of the input [20][21].

Unfortunately, relying solely on mathematical complexity on clustering algorithm alone does not necessarily result in color categorization shared with human. Although the color categorization may be shared among artificial systems and enable them to do certain task very well, it cannot be used for sociable robot.

III. Color Learning through Interaction

A. Approach

This works does not model and simulate human color perception, and does not rely on mathematics for color categorization. In this work, a new approach is adopted, i.e. by making computer learn the categorization through interaction with other members in the society. Although similar to culturalism, in which color categorization is the result of social interaction, they are actually different. Here the computer simply learns categorization from human without ability to create or modify the category by its own. The human, on the other hand, does not develop any new categorization due to the interaction with computer.

In this approach, the computer must have ability to learn and adapt with changing environment, and able to follow the evolution of color categorization. Therefore although at the beginning, it does not know any categorization, eventually through interaction, the color categorization of the computer will reflect the shared color categorization with humans in the society. The rest of this section will describe the architecture of the system developed in this work as well as the interaction mechanism.

B. Perception Space

Perception space defines the colors which can be perceived and how they are organized. Based on which, the color categorization is made. That is why perception space is an important factor to achieve color categorization shared with human. In this work, CIELAB color space, defined by CIE (International Lighting Committee), is used. CIELAB color space is currently the best color space for categorization. Its performance for categorization is found to be better than NPP color space developed based on neuro-physiological data [12]. In addition, CIELAB color space can also handle color constancy to some extent [22].

CIELAB color space has three parameters: L to reflect human lightness perception, a* and b* to reflect opponent channel red-green and yellow-blue in human physiology respectively.

C. Categorization

As for human, the color categorization is evolved and developed depends on the culture and environment. More advanced society knows more color category compared to the primitive ones. Also, for a certain task and environment, more detail color categorization is necessary. For example, an expert on soil will know more detail categorization of brown. Another example, for Eskimos, they know more categorization of blue. To handle this issue, the color categorization for the system is made as hierarchical categorization of the perception space into color basic representation (CBR), color identity (CI) and color category (CC).

Color category (CC) refers to categorization in general, which is commonly identified by color name such as red, blue, green, etc. Color identity (CI) refers to a more specific color categorization. It may be identified by color name such as crimson, azure, etc. However it is also common that color identity does not have any name. For example, a certain color of soil may not have any name, but it is certainly a distinct category. The cluster(s) of CI will form a color category (CC).

Color basic representation (CBR) is the lowest level of categorization. It does not reflect any color categorization in human, but it reflects the color resolution or perceptual discrimination, i.e. the minimum color difference that can be detected and used for categorization. Technically, CBR is also used to reduce the effect of noise and computational load. CBR are made during the design stage and uniformly distributed across the perception space. On the other hand, CI and CC are built during learning process through interaction with human. CI and CC are non uniform and may be overlapped between one and another. The cluster(s) of CBR will form a color identity (CI). In this work, size of each CBR is $5 \times 5 \times 5$ in L, a* and b* directions respectively.

The hierarchical categorization can be represented by the neural network shown in Fig. 1.

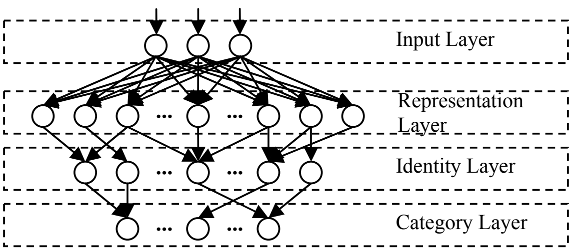

Fig. 1 Neural Network for Color Categorization

The neural network consists of four layers. The first layer is the input layer, which receives the L, a* and b* parameters. The second layer is called representation layer. Each cell in this layer represent a CBR and identified by a certain range of L, a* and b*.

The third layer is called identity layer. Each cell in this layer represents a cluster of CBR. This cluster of CBR is called color identity element (CIe). Each CIe may have a conceptual label or name. A group of CIe having the same conceptual label will form a color identity. The conceptual label itself becomes the name for the color identity. If a CIe does not have conceptual label, it will form a CI by its own. The connection between cells in 2nd and 3rd layer represents whether the CBR belong to the particular CIe. There are two parameters in each connector: Y (yes) and N (no) counters, to measure the confidence level as well as total number of adjustment of the connection. A CBR may connect to more than one CIe. At the beginning there is no cell at all in this layer. The cells and connections are built through interaction.

The fourth layer is called category layer. Each cell in this layer represents a cluster of CIe, which is called color category element (CCe). Most of CCe will have a conceptual label or name. A group of CCe having the same conceptual label will form a color category. The conceptual label itself becomes the name for the color category. The connection between cells in 3rd and 4th layer represents whether the CIe belong to the particular CCe. Two parameters in each connector, Y (yes) and N (no) counters are used to measure the confidence level as well as number of adjustment of the connection. A CIe may connect to more than one CCe. Similar to the identity layer, at the beginning there is no cell at all in this layer. The cells and connections are built through interaction.

Both CIe and CCe are the intermediate categorization to achieve CI and CC. In summary, the complete hierarchical categorization can be seen in Fig. 2.

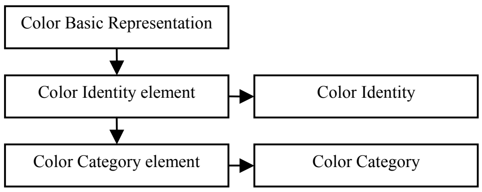

Fig. 2 Complete Color Hierarchical Categorization

D. Interaction

Through interaction, the computer learns color identity and color category, i.e. by building the identity and category layer of neural network. The interaction is done with a human master at one time. The mechanism for each interaction is as follows:

1) Human master will show an image to computer. This can be acquired from webcam or image file. From the image, the human master will select a color to be learnt by computer. This selected color is deliberately chosen by human master, and indicates the color which categorization needs to be known by the computer in the society. The computer will then determine the CBR of the selected color.
2) The computer will show the CC of the selected color having the highest confidence level. The CC is shown by showing the CBR having highest confidence level for each CCe belonging to the particular CC. This category is to be confirmed or denied by human master.

3) If the human master confirms, the particular CC is optimized. Its Y counter is increased, while for other CC, the N counter is increased. This lateral inhibition helps the self organization and minimizes wrong or multiple categorization. The computer will then show all CCe belonging to the CC (in similar way as in #2, i.e. by showing the CBR having the highest confidence level for each CCe) as well as all adjacent CCe which do not belong to the particular CC. For each CCe, the human master will confirm or deny whether it belongs to the CC. Through this confirmation or denial, the category can be reduced or expanded incrementally and the counters, which reflect confidence level, are updated.
4) If the human master denies, the computer will show CC having the next highest confidence level. If it is confirmed, it is then optimized in the same way described in #3.
5) If all CC known by computer are denied, a new CCe is made. It consists of only the CIe where the selected color belongs to. If the CIe is not known, then a new CIe is created instead of CCe which is described in #9. The new CCe is then optimized in the same way described in #3. The human master may also give the conceptual label for this CCe.
6) The computer then will show the CI of the selected color having highest confidence level. The CI is shown by showing the CBR having highest confidence level to each CIe belonging to the particular CI. This identity is to be confirmed or denied by human master.
7) If the human master confirms, the particular CI is optimized. Its Y counter is increased, while for other CI, the N counter is increased. The computer will show all CIe belonging to the CI as well as all adjacent CIe which do not belong to the CI. For each CIe, the human master will confirm or deny. Based on which the identity can be reduced or expanded incrementally and the counters on each connection are updated.
8) If the human master denies, the computer will show CI having the next highest confidence level. If it is confirmed, it is then optimized in the same way described in #6.
9) If all CI known by computer are denied, a new CIe is made. It consists of only the CBR where the selected color belongs to. The new CIe is then optimized in the same way described in #6. The human master may also give the conceptual label for this CIe.

Through the above mechanism, the color categorization are built and developed. The color identity is formed of CIe having the same conceptual label, whereas color category is formed of CCe having the same conceptual label. The conceptual space is also developed through this interaction. Conceptual space is the space in which the computer knows the categorization. Ideally, perceptual space (the space in which the computer is able to perceive) and conceptual space are the same. However, as also happened for human, they can be different. For example, Eskimos have perceptual space like other human being, but their conceptual space may only be developed in blue region. In this system, the integration of all CIe forms the conceptual space for computer.

There is no merging or deletion of cluster, but they can be reduced or expanded. The one with negative confidence level will simply be ignored, but it can be revived through much more confirmation from human master. Each category is built incrementally to ensure the appropriate clustering. It may also help human master during interaction in optimizing the CI and CC.

IV. Results and Discussions

Through number of interactions, the computer learns color categorization and eventually arrives at the color categorization shown in Fig. 3. It has 11 color categories, which consists of 64 CIe. The comparison between computer categorization and human is done only in color category level, as there is no much data on color identity of human. However as the mechanism is quite similar in developing color category and color identity, the analysis can also be valid for color identity.

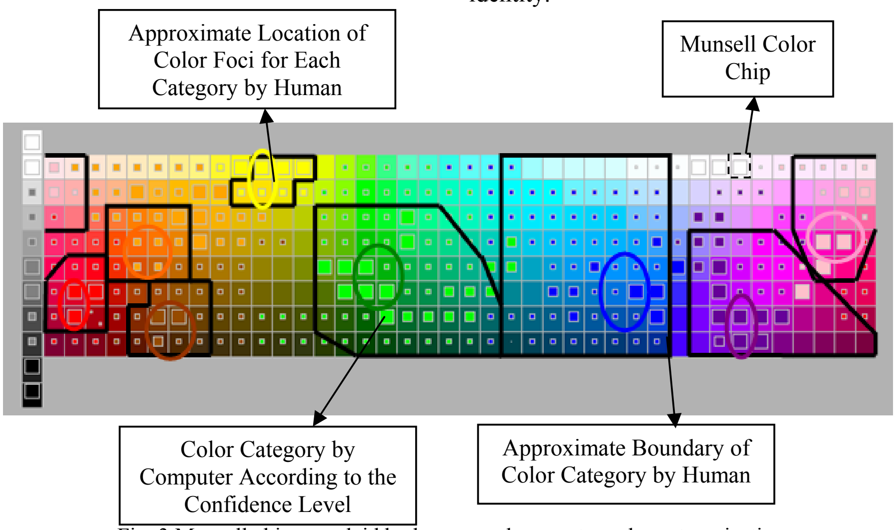

Fig. 3 Munsell chips overlaid by human and computer color categorization

Fig. 3 shows Munsell chips (as also used in [12]) overlaid by both human and computer color categorization. The data of color categorization of computer is obtained after a few weeks of interaction of the system. The categorization is indicated by a rectangular on top of the Munsell chips. The size of the rectangular reflects the confidence level within the same category, but not across categories. The category with a very small or negative confidence level is not shown. Also, if there is more than one category for the color chip, only the most dominant ones are shown.

On the other hand, the data of color categorization of human is obtained from the survey of Berlin and Kay [2]. In this figure, the boundary of each category is represented by a bold border, while the approximate location of color foci for each category is represented by an oval shape. As can be clearly seen, although categorization by machine looks wider, the overall categorization is sufficiently good. There is only a little mismatch categorization between human and computer.

Color foci, which are also known as color prototypes, are defined as the best representation for each category. As for human, it is argued that color foci are innate due to physical characteristic of humans and does not much affected by environment and social interaction [3][23]. However large variation of color foci [24][25] is also found. In this work, color foci are not considered during the design of the system. Interestingly, from this result it is found that the color with highest confidence level by computer is almost the same as the color foci from Berlin and Kay's data. This indicates that it is not necessary to consider whole aspects of human color perception as they may also be obtained as the result of interaction.

This is happened because for color foci, the number of denial is very little and only occurred when the number of interaction is very small. As the number of interaction increases and the correct categorization is known, human master will always confirm it, which results in very high confidence level. It is different with the color in boundary of categorization, where number of confirmation and denial are both high as the number of interaction increases. However if the system rarely exposed to the color foci, but mostly to another unambiguous color in the category, confidence level for the color foci is not the highest, such as in orange.

Through confirmation and denial by human, the computer learns and at the same time mimics the color categorization from human. This makes computer have the shared color categorization. However the performance of the system highly depends on variation of exposed color, where the system may only be exposed to certain color all the time, and error made by human either intentionally or not. This system can be improved by implementing social status role during interaction. The one with higher social status will have more influence compared to the lower one. This may help to reduce the effect of human error.

The learning process is quite slow, however after the learning process all the data can be copied to another computer. Hence for the new machine, it is not necessary to learn from scratch. It can use the already learnt categorization by other machine as the basis of further learning. Not only for color categorization, but this may also be valid for machine intelligence in general.

Although the computer is able to have the shared color categorization, it is still far to be implemented for color vision in sociable robot. Shared color categorization is not enough. Sociable robot, to live coexist with human in real environment, will face various lighting condition and surface context which affects the color dramatically [26]. Preprocessing color for the basis of categorization is necessary. In addition, as sociable robot will not only handle color, the modality with other features and sensors must also be taken into consideration.

V. Conclusion

In this paper, the work to enable computer learn color to have the shared human color categorization through interaction is presented. The result shows that, without following human color perception and much mathematical complexity, the computer is able to learn color and eventually arrive at the shared human color categorization. Color categorization by computer, even for sociable robot, is not necessary to be constrained by human color perception. Machine color perception is different with human color perception. And interaction may serve as bridge to achieve human-like knowledge and intelligence by machine. The overall system and interaction mechanism can still be improved further.

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