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A fuzzy logics clustering approach to computing human attention allocation using eyegaze movement cue

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Abstract

Human's attention is an important element in human–machine interface design due to a close relationship between operator's attention and operator's work performance. However, understanding of operator's attention allocation while he or she is performing a task remains a challenging task because attention is generally unobservable, immeasurable, and uncertain. In our previous study, we demonstrated the effectiveness of using operator's eye movement information to understand attention allocation, which has made attention observable. The present paper describes our study which addressed immeasurability and uncertainty of attention. Specifically, we used eye fixation's duration to indicate operator's attention and developed a new computational model for the attention and its allocation using fuzzy logics clustering techniques. Along with the development of this model, we also developed an experiment to verify the effectiveness of the model. The result of the experiment shows that the model is promising.

Keywords: Human–machine interaction (HMI); Eyegaze tracking; Visual attention allocation; Fuzzy clustering

1. Introduction

Despite its importance, understanding of operator's attention allocation behavior when he or she operates on an interface under a certain environment remains a challenge. The root causes of this challenge come from the inherent characteristics of human attention including (1) human attention is unobservable—there is no reliable way to "see" human attention (Harré, 2002; Gonalves et al., 2000), (2) human attention can hardly be measured or quantified—there is neither a physical unit to describe human attention nor a method to infer the state of attention (Wu et al., 2005; Horvitz et al., 2003), and (3) human attention is expressed in an uncertain or vague manner—there is no definite boundary between "concentration" and "distraction" for attention. In the case of attention to the interface through a visual modality, it is not possible to describe an exact region where attention falls (Brown et al., 2003).

With regard to the unobservability of human attention, the recent research suggests that the eye movement information can implicitly indicate the area of user's attention (Hess et al., 1998). There are several studies on using eye movement parameters to understand operator's attention allocation (Goldberg and Kotval, 1998; Smith et al., 2003; Lin et al., 2003; Chambers and Mattingley, 2005; Roda and Thomas, 2006; Le Meur et al., 2006). These studies have concluded (i) eye movements may yield important clues to human attention allocation at a fine temporal grain size typically on the order of 10 ms, (ii) data about eye movement can be collected non-intrusively, and (iii) eye movement parameters can serve as a sole source of information or as a supplement to other sources like verbal protocols (VP), electromyography (EMG), electroencephalogram (EEG), etc.

Measurement of human attention allocation based on eyegaze tracking has been studied by some other researchers (Treisman, 1986; Itti and Koch, 2001; Quek et al., 2002)

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including ours (Lin et al., 2003). Information from eye movements includes eye fixations, eye saccades, pupil size, blink rate, eye vergence, etc. Our previous study has shown that eye fixation is one of the important indicators among them (Lin et al., 2003). Eye fixations are pause in the eye scanning process over informative regions of interest. Measures of fixation include fixation duration—the time spent on an area of the visual field (also known as dwell time) and the number of fixations—the number of times the eye dwells on an area of the visual field. The longer fixation duration may imply the more time spent on cognition of a target. Eyegaze fixation is negatively correlated to the efficiency of task execution; particularly a more number of fixations imply that more information is required for performing a task. Eye fixation can thus be used to infer attention state as well as its allocation.

Attention allocation behavior is related to both task performance and interface design in such a way that given a particular interface design and a particular class of task, there will be a particular attention allocation behavior which further corresponds to task performance. As such, different interface designs can be evaluated in terms of attention allocation behavior. Furthermore, if a standard attention allocation behavior for a class of task is given, it is possible to adapt an interface to individuals to meet this standard behavior. This makes sense for adaptive interface to individuals for a class of task. Therefore, it is very useful to quantify attention allocation behavior, which is a primary motivation for our study.

Our study was based on an assertion that human's (visual) attention to a particular piece of knowledge or information displayed on an interface media will not be "crisp" or exclusive to that piece; in other words, the neighboring elements of that piece may occupy the attention as well. This assertion seems to be shared by Treisman (1986) who suggested that processing outside of focus is only "attenuated" (weakened) not stopped entirely. Thus, in our study, we considered that such a boundary is vague, and we developed a model to capture this vagueness by applying fuzzy logics clustering techniques. The model was applied to a plant operation problem and thus it was validated. Our model differs from those in the literature (Itti and Koch, 2001) in that we applied fuzzy logics clustering techniques which we believe to be the most natural fit.

The organization of the paper is as follows. Section 2 presents a model of attention based on eyegaze fixation. Section 3 presents a fuzzy logics model of human attention with respect to an entire interface. Section 4 presents a method to compute attention allocation strategy, and Section 5 presents a method to compute the pattern of attention which is further related to task performance. In Section 6, an experiment is presented to illustrate how our approach works and validate it. Section 7 concludes the paper with a brief discussion of future work.

2. A model of human attention with respect to visual elements

Our study assumed a particular task performing context where the attentional focus on a displayed element is exclusively in align with the element the eyegaze focuses. Fig. 1 shows a conceptual model of the visual attention based on this assumption where there is a single direct connection (which represents a perception from a perceptive of cognitive effectiveness) between the eye and interface (element)—called single eye–interface connection. Further, we considered that all points on the interface display can potentially be eye fixation points.

Assume that a random variable X_P represents a connection on point P on the interface display. X_p takes two values: 0 or 1. If the event "*point P is an eye fixation point*" occurs, then $X_p = 1$ (which implies there is a connection); otherwise, $X_p = 0$ (which implies there is no connection). Further, let D_P be the fixation duration on point P and D_{total} the total fixation duration during an active task performing period associated with the connection. The strength of the connection with respect to point P (W_P) is defined as $W_P = D_P/D_{total}$. We further defined the degree of attention (A_P) as the same as the strength of the eye–interface connection in the case of the single eye–-interface connection, namely

$$A_P = W_P = \frac{D_P}{D_{total}} \tag{1}$$

Consider the following situation: given an eyegaze and a point P on the interface display, there will be some other information elements on the interface display that occupy the attention per se (see Fig. 2). In Fig. 2, we show that an eyegaze connects to P while the eyegaze also connects to a set of neighboring points P_i ($i = 1, 2, \ldots, n_p$, where n_p: the total number of P's neighboring points). It is reasonable to assume that the connection between the eyegaze and P_i should be relatively weak. Thus, the degree of attention on a point P is defined as the sum of the strengths of the strong eye–interface connection and of all the weak eye–interface connections. Let ${A_P}^{S-EI}$ the strength of the strong eye–interface connection on P and ${A_P}^{W-EI}$ be the strength of a weak eye–interface connection. We have

$$A_P = A_P^{S-EI} + \sum_{i=1}^{n_P} A_{P_i}^{W-EI} \tag{2}$$

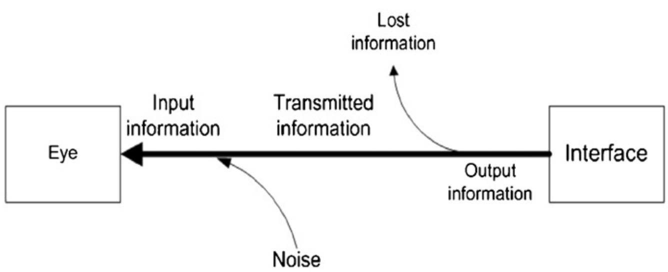


Fig. 1. Single eye–interface connection.

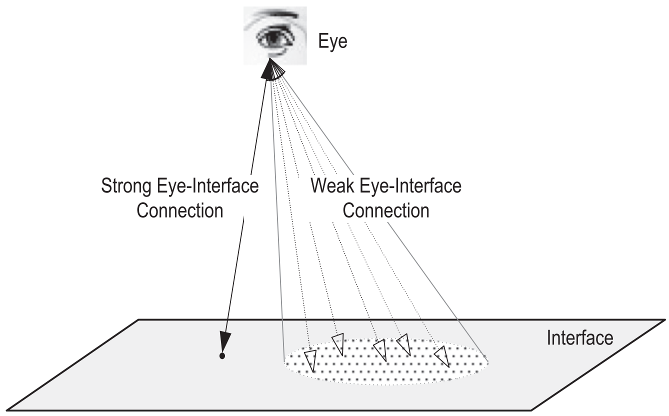


Fig. 2. Eye–interface (EI) connection (strong eye–interface: S–EI; weak eye–interface: W–EI).

We call the conceptual model as illustrated in Fig. 2 multiple eye–interface connection.

3. A model for human attention with respect to an interface

Interface can be viewed as an artifact which is composed of a set of information elements or components which are connected in a certain way to bear semantics or meaning. When the eyegaze falls onto a component (which has meaning or semantics), we say that attention is established on this component—in other words, a cognitive activity is performed on the semantics of this component. Further, as we discussed before, it is inevitable that the eyegaze may be attracted by components surrounding that component, which leads to vagueness in expressing the degree of this attraction. In the following, we will show how this vagueness can be represented.

Suppose that we can classify all eyegaze points which fall onto the components of an interface display; that is to say, we have a set of classes C. To cope with the vagueness as we mentioned, we change a paradigm of logics in such a way that we introduce a membership function for each eyegaze point. As such, that an eyegaze point falls onto a class will be described by a degree of membership which takes any value from 0 to 1. This implies that for the strong eye–interface connection with respect to an eyegaze point to an interface component, the degree of membership function associated with this component will be higher than that for the weak eye–interface connection.

The above discussion implies that a fuzzy clustering technique (James, 1981; Höppner et al., 1999; Duda et al., 2001) should be best applied to classify the eyegaze points. With the concept of fuzzy clustering, an element can belong to more than one cluster or class—the key here is the membership function for each class. Therefore, the fact that an eyegaze point may be attracted to more than one semantic component can be well represented. In the following, a fuzzy clustering approach to the classification of the eyegaze points is presented. It is noted that our approach is adapted from those studies by Melin and Castillo (2005) and Yager and Filev (1994).

Each eyegaze point corresponds to a 2-tuple of numbers (x,y) where x and y are the coordinates of a point on the interface display. Let P be a set of eyegaze fixations, $n=|P|$ be the number of eye fixations. The element of P, which is an eyegaze fixation, can be denoted as $p_{(x_i,y_i)}(0<i<n)$. Thus, $P=\{p_{(x_1,y_1)},p_{(x_2,y_2)},\ldots,p_{(x_n,n)}\}$. Also, let C be a group of clusters or classes which correspond to interface components, $l=|C|$ be the number of clusters and $c_j(0<j<l)$ be the centers of the clusters. A partition $\Lambda=\{C_1,C_2,\ldots,C_l\}$ of P is a "soft partition" if and only if the following two conditions are satisfied:

(i) For all $p_{(x_i,y_i)}\in P$ for all $C_j\in\Lambda$, there is $0\leqslant\mu_{p_{(x_i,y_i)}\to c_j}\leqslant 1$;
(ii) For all $p_{(x_i,y_i)}\in P$, there exists $C_j\in\Lambda$ such that $\mu_{p_{(x_i,y_i)}\to c_j}>0$.

Where the expression $(\mu_{p_{(x_i,y_i)}\to c_j})$ denotes the degree of membership of an eyegaze $p_{(x_i,y_i)}$ on a point $(x_i,\ y_j)$ of C_j.

In the following, we discuss how to determine the membership function $\mu_{p_{(x_i,y_i)}\to c_j}$ of all eyegaze points $p_{(x_i,y_i)}$ with respect to all clusters C_j. The approach is to minimize the following objective function, J_m, which is defined as follows:

$$J_m(\Lambda,V)=\sum_j\sum_i\mu^m_{p_{(x_i,y_i)}\to c_j}||p_{(x_i,y_i)}-c_j||^2 \tag{3}$$

where m is a weight that determines the degree to which partial members of a cluster affect the clustering result, and V stands for a matrix, the elements of which are membership functions. In the following, we give an algorithm to determine the membership function.

Step 1: Initialize $C=\{c_1,c_2,\ldots,c_l\}$.

Step 2: $C^{old}\leftarrow C$.

Step 3: Calculate the membership functions with the following equation:

$$\mu_{p_{(x_i,y_i)}\to c_j}=\frac{1}{\sum_{k=1}^{c}(|p_{(x_i,y_i)}-c_j|/|p_{(x_i,y_i)}-c_k|)^{2/m-1}} \tag{4}$$

Step 4: Update c_j in C using the following equation:

$$c_j=\frac{\sum_{k=1}^{n}(\mu^m_{p_{(x_k,y_k)}\to c_j}p_{(x_i,y_i)})}{\sum_{k=1}^{n}\mu^m_{p_{(x_k,y_k)}\to c_j}} \tag{5}$$

Step 5: Calculate $E=\sum_j||c^{old}-c_j||$.

Step 6: If E is greater than a preset threshold ε, then go to step 2.

Step 7: If E is less than a preset threshold ε, then produce the final result C and μ.

It should be noted that some parameters in the above algorithm need to be determined, which can be done by applying the algorithm to a particular application interface. In particular, (1) the number of clusters is simply the number of key components on the interface display, (2) the Euclidean distance is employed, (3) the initial cluster center is set to the center of the key interface components, and (4) the weight m is set to be 2.0 which is based on our experience in applying this algorithm to an application problem.

Let $A_{p_{(x_i,y_i)}}$ be an eyegaze fixation point $p_{(x_i,y_i)}$ and $\mu_{p_{(x_i,y_i)}\to c_j}$ is the degree of membership to which point $p_{(x_i,y_i)}$ belongs to a cluster c_j. Then, the degree of human attention based on the eyegaze fixation, A_{c_j}, on a particular component c_j can be computed by

$$A_{c_j} = \sum_{i=1}^{n} A_{p_{(x_i,y_i)}} \mu_{p_{(x_i,y_i)}\to c_j} \quad (6)$$

4. A model of attention allocation strategy

Human's cognition strategy is associated with attention allocation strategy. The attention allocation strategy is the attention distribution over interface components through a period of task performing processes or attention allocation processes. Since the attention to an interface at a particular time can be represented with Eq. (6), the attention allocation strategy in a period of task performing processes can then be represented by a matrix $\boldsymbol{A} = [A_{C_1} \quad A_{C_2} \cdots A_{C_l}]$. This matrix is similar to the block encoding technique proposed by Huffman (1952) who called it codeword. Therefore, in the following, we call $\boldsymbol{A}$ attention codeword.

Fig. 3 is flow chart which summarizes all the steps to compute attention codeword for an entire period of cognitions performed by a human operator on an interface. From this figure, we can see that at the end of the process, we are able to compute a human's attention allocation strategy which is further represented with attention codeword.

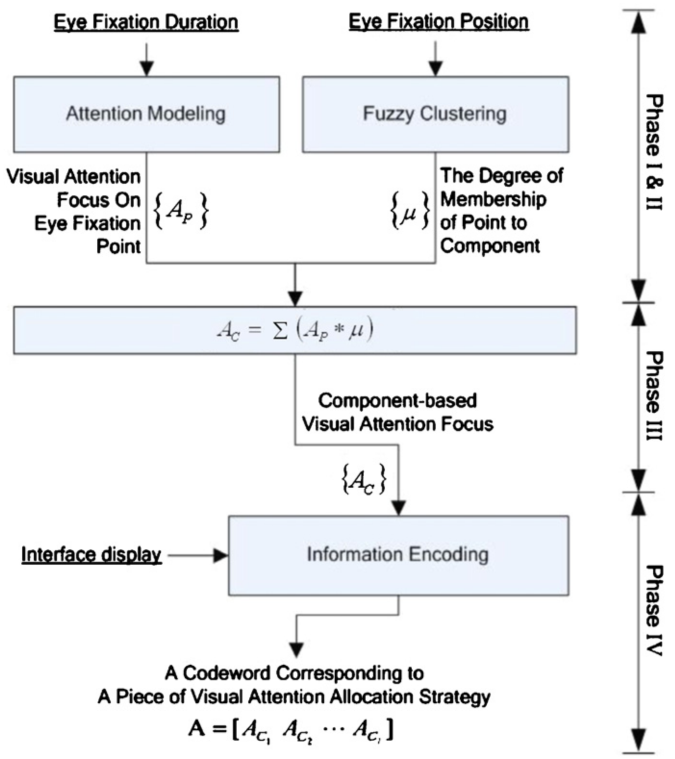


Fig. 3. A novel method to compute attention allocation strategy based on eye fixation.

5. Computing attention allocation strategy pattern

Human's attention strategy is further related to human's performing a task and interface design, as the task is performed on the interface. Given an interface design, evaluation of the design requires that human subjects perform task on the interface. It is possible that we can find the patterns of operator's attention allocation strategy which are correlated to task performances. Such a relationship can help the human–machine interface design and human–machine interaction management in two ways. The first way is that we can select operators based on whether their attention allocation strategy patterns match with the pattern which corresponds to the best task performance. The second way is that we can optimize the interface design in terms of the best task performance achieved by the operator with a certain attention allocation strategy pattern.

The relationship between human's attention allocation strategy pattern and human's task performance can be found through the measurement of human's attention allocation strategy and human's task performance. The attention allocation strategy patterns can further be obtained by the clustering techniques such as the hierarchical clustering technique. The advantage of the hierarchical clustering technique is such that it can investigate groupings in chaotic data—in particular by creating a cluster tree such that we are able to probe the number of clusters without any knowledge in advance (Duda et al., 2001); nevertheless, any other clustering technique can be applied here such as the K-means clustering technique.

6. Illustration and preliminary validation

6.1. Experiment

6.1.1. Human–machine interface: DURESS

A thermal-hydraulic process plant system called the Dual Reservoir System Simulation (DURESS) was taken as the example. DURESS was initially prototyped by Vicente (1991) for illustrating and validating the ecological interface design framework (Vicente and Rasmussen, 1992; Vicente et al., 1995); see Fig. 4. More detailed information of the system could be found in Lin et al. (2003) and Lin and Zhang (2004).

The DURESS system consists of the following components: VA and VB stand for input valve control, PA and PB for pump control, R for reservoir, VO for output valve control, H for heater control, T for temperature indicator, FWS for the feedwater stream, and OWS for output water stream. The meter beside each valve gives a reading of the flow rate.

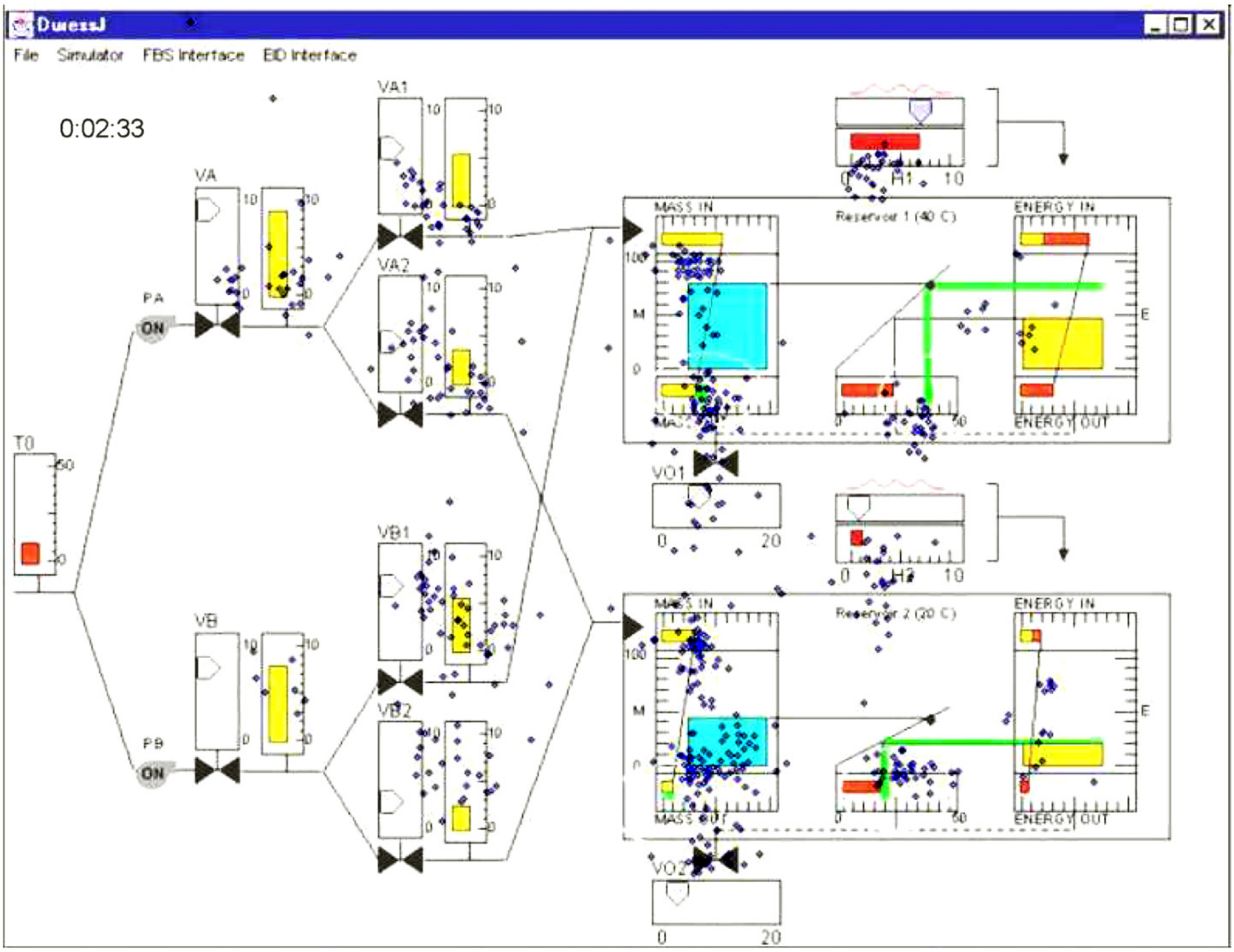


Fig. 4. EID–DURESS interface and eyegaze tracking experiment.

The goal of the system is to maintain the desired temperatures ($DT1 = 40\,°C$, $DT2 = 20\,°C$) and desired flow rates ($DV1 = 8\,kg/s$ and $DV2 = 2\,kg/s$) of the water out of the two reservoirs at OWS1 and OWS2, respectively. To achieve these goals, one needs to control two pumps (PA, PB), eight valves (VA, VA1, VA2, VB, VB1, VB2, VO1, VO2), and two heaters (H1, H2).

6.1.2. Participants

The participants involved in the experiment were students at the College of Engineering, University of Manitoba. Potential candidates who showed interests in participating the experiment and applied were carefully interviewed, and in some cases, reference evaluations of the applicant's reliability and responsibility were requested to ensure experiment control. Considering representativeness of the experiment, all participants had to pass the required credits in thermal fluids courses in a 4-year engineering program and were associated with engineering disciplines.

The gender issue was considered as well. In our previous human–machine system studies where manual control still prevails, e.g., vehicle driving (Lin et al., 2005), the gender factor may be significant. In applications of computer user interfaces, the significance of the gender factor remains an open question.

As a result of the selection process, there were 20 students (6 females and 14 males, from the University of Manitoba) participating in the experiment. The average age of the participants was 31. Of the participants, 3 were undergraduate students and 17 graduate students. All had the background described above. The participants were paid for their participation of the experiment.

6.1.3. Apparatus and procedure

A Tobii $\times 50$ Eye Tracker was used for recording and analyzing operators' eye movement behavior. This apparatus is mounted on a rigid headrest for greater measurement accuracy (less than 0.5° on the fixation point). The Clearview software package is used for recording and analyzing the eyegaze data. This software provides flexible tools for synchronized data collection and visualization. It is noted that a preliminary data collection of this experiment was conducted by using an Eyegaze system from LC Technologies. More details about the experiment were documented in our previous work (Lin et al., 2003).

Experiments were conducted in the EID–DURESS shown above. The participants were asked to control the system (including adjust the openings of the valves and the heaters) until reaching the dynamic equilibrium (the demanded temperature and flow rate of the water out of the reservoirs) as quickly as possible. The participants were required to perform three replications for each trial. As a result, in total there were 60 runs for the entire experiment. The collected data corresponds to 60 different pieces of human visual attention allocation strategies.

For simplicity but without loss of generality, the experimental data of replication 2 from subject 17 on the EID–DURESS is considered as an example to illustrate the concepts and ideas of our proposed above method to compute human attention allocation (Lin et al., 2003).

6.2. Attention allocation inferring method

6.2.1. Step 1: eye–interface connection

The duration time of each eye fixation on EID interface display is used to calculate visual attention focus on the current eye–interface connection. The detailed result is shown in Fig. 5. Fig. 5(a) is a scatter plot of all eye fixation points on the interface display (the *XY* surface is the corresponding plane of the display interface). Fig. 5(b) is a 3D plot of visual attention focus on all of eye fixations, in which *XY* surface is the interface display and the *Z*-axis is the duration ratio. Fig. 5(c) provides a detailed visual attention focus on all eye fixations in a small rectangular region, whose vertices are (380, 435), (420,435), (420,475), and (380,475), respectively.

6.2.2. Step II: fuzzy clustering based on interface display

In the second step, fuzzy clustering is conducted for finding the degrees of membership of all eye fixation points belonging to interface components. Here, the information about the position of eye fixations and interface components are used. There are 14 components in the interface display: PVA, PVB, VA1, VA2, VB1, VB2, M-VOL1, M-VOL2, H1, PRC1, H2, PRC2, ENER1, and ENER2 (Lin et al., 2003; Lin and Zhang, 2004). In this case, each eye fixation point has its own degrees of membership to these 14 components. For example, the degrees of membership for Point (445, 468) to each of these components are (see Table 1).

From Table 1, it can be seen that the point has the strongest link with component M-VOL2 (with the degree of membership 0.941350). This means that most of visual attentions on this point can be accumulated as a part of visual attention on component M-VOL2. Note that the sum of all degrees of the membership of a point to all components is 1. Fig. 6 shows an example of the membership function of components M-VOL2 on the interface display, in which interface-*X* and -*Y* represent the geometrical dimensions of a display and the spatial information of an interface component say M-VOL2 is thus measured along these dimensions.

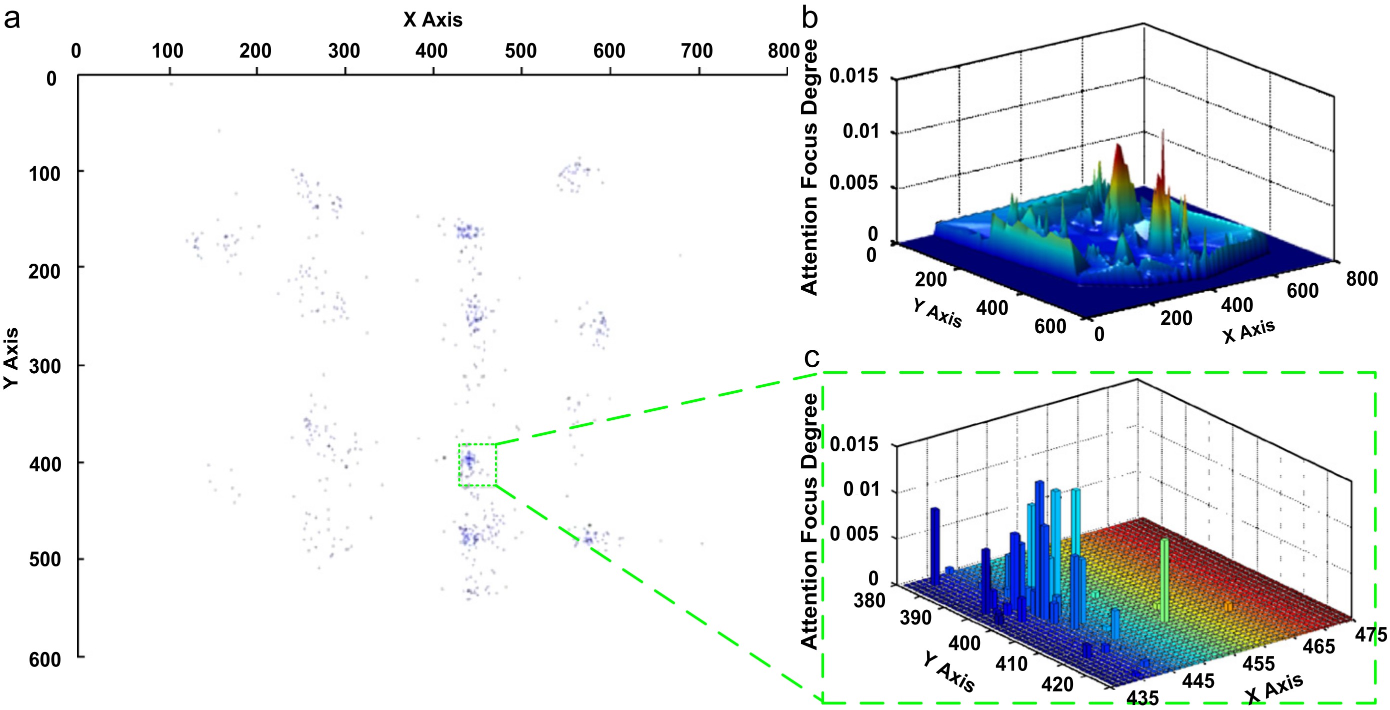


Fig. 5. Visual attention focus distribution (EID interface, subject #17, replicate #2): (a) scatter plots on all eye fixation points; (b) attention Focus on all eye fixations points; and (c) attention focus on the points in a small rectangular region (adapted from Lin et al., 2003).

Table 1
Degree of membership on different components.

Component	PVA	PVB	VA1	VA2	VB1	VB2	M-VOL1
Degree of membership	0.003085	0.010201	0.000401	0.017365	0.000349	0.000687	0.000945
Component (cont.)	M-VOL2	H1	PRC1	H2	PRC2	ENER1	ENER2
Degree of membership (cont.)	0.941350	0.002081	0.019643	0.000404	0.000645	0.001573	0.001270

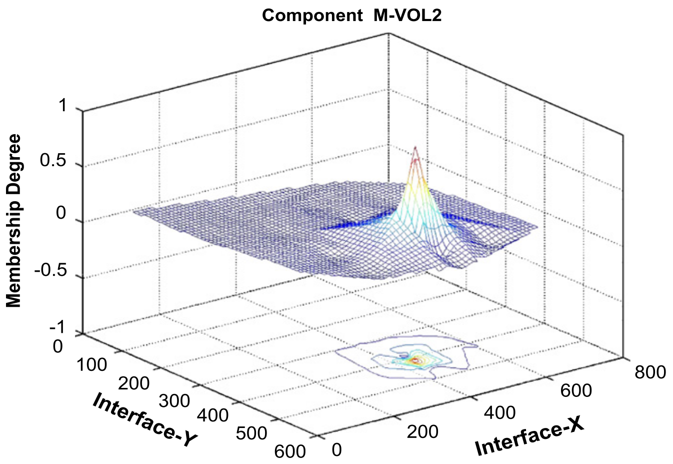


Fig. 6. Membership function of component M-VOL2 as a result of fuzzy clustering.

The performance of the above clustering can be evaluated using the objective function J_m. In particular, the algorithm runs after 80 iterations, J_m converges to a minimal value 0.4 (i.e., the distance from data points to cluster centers is minimized).

6.2.3. Step 3: component-based attention

In the third step, the degree of visual attention on each component can be calculated using Eq. (6). Fig. 7 shows the values of visual attention focus on all the components in the DURESS interface. From this figure, it can be seen that most of visual attentions are being allocated on component M-VOL2, whose degree is 0.1507. The second and third components are attracting attention focus are M-VOL1 and VA2, whose degrees are 0.1035 and 0.0963, respectively.

6.2.4. Step 4: attention codeword

In the last phase, using information encoding, a codeword representing a piece of human visual attention allocation strategy is constructed by assigning all degrees of visual attention focus on the interface components into the corresponding fields as shown in Fig. 8. Note that this step is optional. The constructed attention codeword may be used as an input of a classifier for extracting patterns of human visual attention allocation strategy.

6.3. Step 5: extracting human attention allocation pattern

The above steps were applied to each component (14 in total) of EID–DURESS interface display, resulting in the clustering result of the entire interface. In particular, three different patterns of visual attention allocation strategies were obtained. The first pattern is to allocate most of visual attentions on component "M-VOL2", which has 58.33% of all strategies. The second and third patterns are focusing most of attentions on Component "Principle1" and "M-VOL1", which have 26.67% and 10%, respectively, of all strategies. The remaining patterns that cannot be recognized are about 5%.

Further, the problem of how the attention allocation strategy affects task performance was studied. In order to evaluate task performance, two criteria were applied: (1) success to make the system lead to dynamic equilibrium of the DURESS (the water with the demanded temperature flows out of the system at a constant rate) and (2) the average operation duration and its standard derivation (only investigate the strategies that reach dynamic balance). Based on these criteria, we obtained the following result. Among three attention allocation strategies, in the first one, (1) 82.86% of them can reach dynamic equilibrium and (2) the average operation duration for reaching dynamic equilibrium is about 135.43 s and its standard deviation is 42.12 s; in the second one, (1) 81.25% of them reach dynamic equilibrium and (2) the average operation duration for reaching dynamic equilibrium is about 176.06 s and its standard deviation is 60.23 s; and in the third pattern, 33.33% of them can reach dynamic equilibrium and the average operation duration is about 331.33 s and its standard deviation is 76.79 s. This result evidenced that different strategies of visual attention allocation have their distinctive performance characteristics.

7. Conclusion and future work

The study has made effort on developing a quantitative method to measure human visual attention allocation with consideration of vagueness in attention expression or representation. Further, the study has developed a method to extract human attention allocation pattern. An experiment was conducted to illustrate the proposed method and to provide validation for the proposed method. This study concludes (1) the proposed multiple eye–interface connection model is promising, (2) it is possible to capture the uncertainty of human attention allocation in a computational manner, and (3) the relationship between attention allocation strategy and task performance can be revealed.

There are a few limitations of in the present study which is leading to our future work as follows. The first limitation

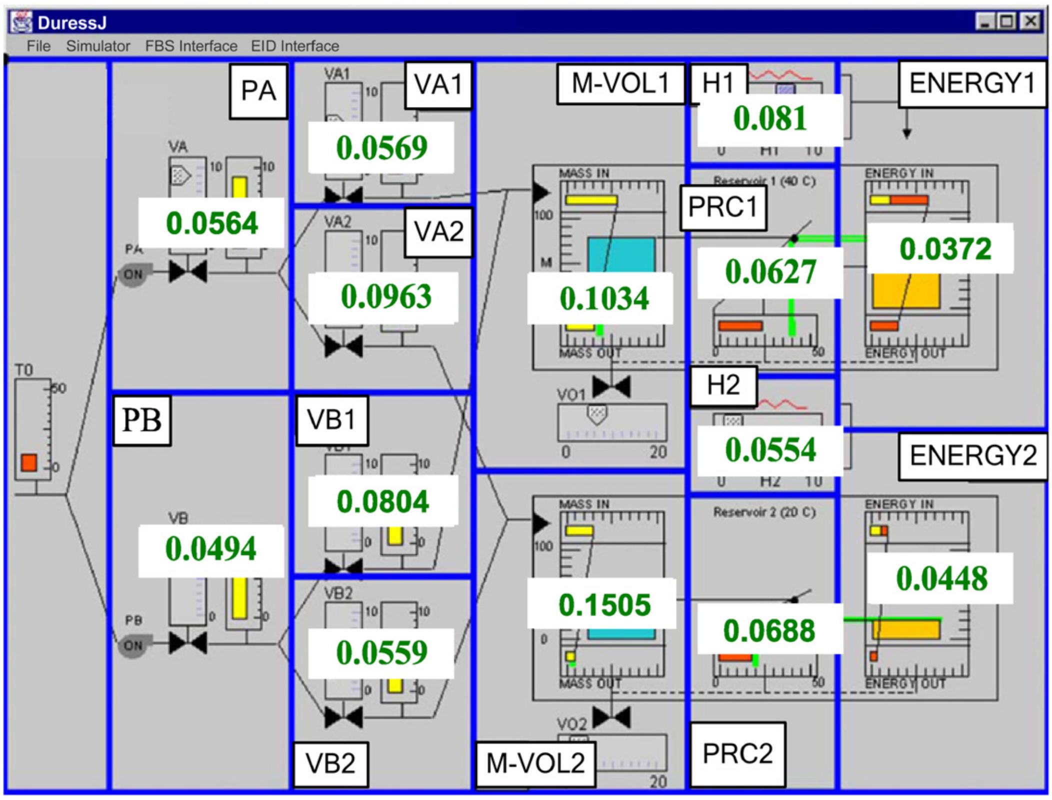
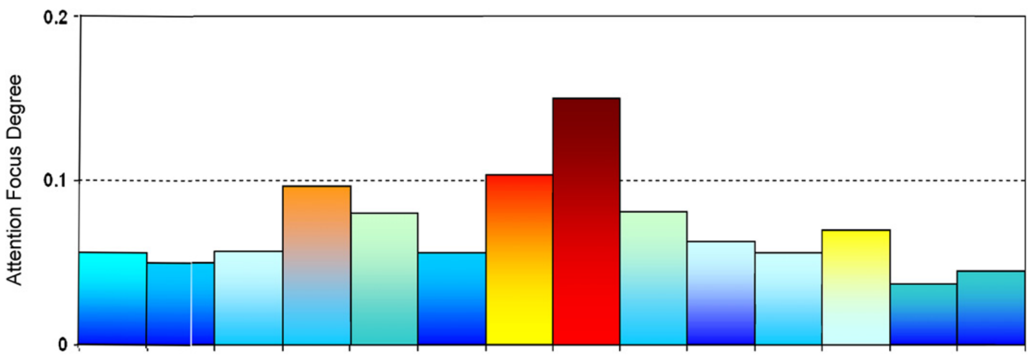


Fig. 7. Visual attention allocation on the displayed components.



PVA	PVB	VA1	VA2	VB1	VB2	M-VOL1	M-VOL2	H1	Prc1	H2	Prc2	Energy1	Energy2
0.0565	0.0494	0.0569	0.0963	0.0806	0.0559	0.1035	0.1507	0.0810	0.0627	0.0554	0.0691	0.0373	0.0448

Fig. 8. An example of attention codeword and its visual representation.

is related to capturing of uncertainty of human attention using the eyegaze tracking technique alone. There is no doubt that eyegaze tracking is an excellent tool, but in some cases the eyegaze fixation cue alone may not completely infer human attention. For example, when an operator's eyegaze dwells on an interface element, this may not necessarily mean that he or she is performing a cognitive task which is relevant to this particular interface element. Therefore, it should be better to apply other cues, such as physiological signals or task performances together with the eyegaze fixation cue to infer human attention allocation as well as allocation pattern. The second limitation is that the case study is still at a preliminary stage and more experiments from other human–machine interaction applications are needed in order to generalize the research findings about our method. This leads to one of our continuing research efforts, which is to combine eyegaze tracking with other human physiological measurements (e.g., ECG, EEG) (Lin, et al., 2006, 2007) and facial expression (Huang and Lin, 2008), as well as multimodality inferring of human cognitive states (Yang et al., 2008) towards a more accurate and comprehensive inference of human attention and cognitive activity. We also plan to apply this method to study other exciting applications such as medical applications. For example, the proposed method has potential to advance the understanding of patients who suffer from Attention Deficit Hyperactivity Disorder.

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