Fog-Based Human-Interactive Intelligent Monitoring System

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Abstract — **In order to assist people's everyday life more precisely, intelligent monitoring is necessary to reduce human efforts on watching monitor screens. For the changing environment, making decisions only on target recognition by fixed model is not sufficient at all, which is difficult to increment the knowledge and also neglect the implicit valuable information hidden in association between people and the surrounding objects. In this paper, inspired by human interactive learning model, we propose a human-interactive intelligent monitoring system which can autonomously learn people's habits according to the human-object-time association rules day by day, guided by human's expert knowledge at childhood stage or while getting in confused. Depends on its observations and learnt knowledge, while some anomalies happen, give real-time response. Without any prior knowledge in advanced, make it keep learning after observations from user's environment, the precise and customizable services can be provided to every different user. Due to the advantages of Fog Computing, multi-tier fog structure is involved to deal with the analytics and transmission of the huge volume of data to achieve real-time responses.**

I. Introduction

In order to assist people's everyday life more precisely, intelligent monitoring is necessary to reduce human efforts on watching monitor screens. For the changing environment with different user entering and exiting, and unique objects in smart homes and smart offices, in order to reduce human efforts as much as possible and keep the same quality of monitoring, smartening monitoring system is necessary. In order to address the limitations of fixed supervised model, and make machine intelligent enough to deal with changing situation in people's everyday living, researchers are working to propose various human-environment interaction mechanisms [1, 2]. However, most of the human-interactive technology researches, either emphasize on human's face learning or on appliance/object usage rules, none of them combine human, object, and time information and the association rules. Therefore, we propose a vision based intelligent monitoring system with human-interactive learning process, both recognition and human-object-time association rule generation are able to support the dynamic knowledge creation and updating, and the system will be suitable for every different user's needs.

Fog computing [3, 4, 5], is a horizontal and system level architecture, which distribute traditionally centralized Cloud computing operations, such as computing, storage, control and networking, closer to the end users along the Cloud-to-Things continuum. Due to its advantages on latency reduction, the multi-tier fog structure is involved to support our system to achieve almost real-time services.

II. Background Technology

Numbers of the background technologies are involved as base for our system. First, we use SIFT [6] to extract feature points from the target images instead of training a feature extractor model in advanced. Thereafter, an unsupervised and incremental learning structure, Fuzzy ART [7], and the main concepts are described below. Then, sequential pattern tree and support-confidence framework are introduced respectively for mining the potential association rules.

Some of vision based applications with image matching or object recognition, use SIFT, which was proposed by David Lowe, to extract distinctive feature points that are robust against changes in translation, rotation, and scaling, and partially robust against illumination variation. SIFT has proved its superiority to several other known similar methods. By SIFT, after two main functions, feature point extraction and descriptor representation, we can get a 128 dimensional vector as descriptor for each feature point of the target image.

For learning model, we choose Fuzzy ART as base due to its ability for online learning and recognition with known and unknown things like human's face or object, which means it has the characteristics of both stability and plasticity [8]. The typical structure of Fuzzy ART contains three main layer, input layer, comparison layer, and recognition layer. Once input data is presented to the model, through calculation of similarity between the input data and existing categories which stored in the model, make the classification, then update existing knowledge or create the new one.

After recognition on target image, the events about human's daily life can be discovered, and the order of the event sequence are the critical factor to learn human's habits. Therefore, we introduce sequential pattern tree from [9] to store those recognized events in a sequential pattern form to keep the order information between the happened events in an efficient way.

Finally, support-confidence framework [10] is well-known for generating association rules of form $\{X \to Y\}$, where Support $s_{X\to Y}$ represents that the percentage of transactions, which contains $X \cup Y$ transection, in whole transaction database, and Confidence $c_{X\to Y}$ represents that the percentage of the probability of the transactions which contain $X \cup Y$ in whole transaction database and the probability of the transactions which contain X in whole transaction database.

All of the above background technologies are used to support our system and some of the modifications are elaborated in the following section.

III. Proposed Method

Inspired by human interactive learning model, our proposed Fog-based human-interactive intelligent monitoring system is shown in Fig. 1. It starts from Data Layer, by using cameras to collect raw video data, which is the continuous data from the environment, and then in Information Layer, applying human-interactive and incremental object/human recognition for recognizing the object/human that already learnt in database and learning new object/human in the environment with human's preferences. Depending on the information about human, object, and time, the deviation detection can be achieved by comparing with the frequent sequential human-object-time association rules that are explored from historical information in Knowledge Layer, i.e., checking whether there is any event happen beyond the rules. Depending on user's application, it can automatically give user a real-time response when some deviation events detected in Application Layer, and then according to human preferences, feedback the new patterns, temporarily store new ones and those without deviation as candidate patterns. Those patterns would be uploaded to cloud for generating frequent sequential human-object-time association rules, which indicates that who and what object appear or is taken at some time is normal or not, and this part are comprised of frequent sequential pattern mining and association rule generation. Finally, updating the rules for deviation detection. This loop type human-interactive learning process keeps all the knowledge in both recognition part and rule generation part updating and enhancing in accordance with people's daily life.

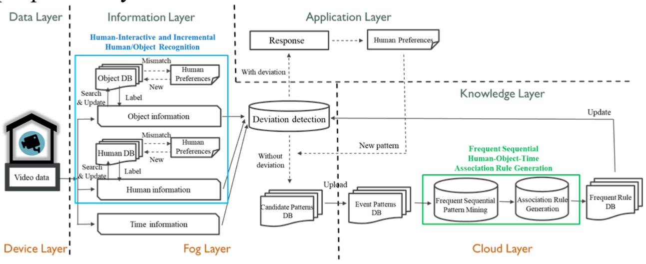

Fig. 1 System architecture of our proposed system.

- Human-interactive and incremental human/object recognition

When it comes to vision based intelligent system, human/object recognition is the indispensable ability. Based on SIFT and Fuzzy ART, the feature points of target images can properly be extracted by SIFT, and Fuzzy ART with both stability and plasticity characteristics, can deal with unsupervised online learning and recognition. For our case, in order to achieve human-interactive and incremental human/object recognition, the above two methods are necessary, and we propose SIFT-ART interactive learning model by combining SIFT and Fuzzy ART, as shown in Fig. 2.

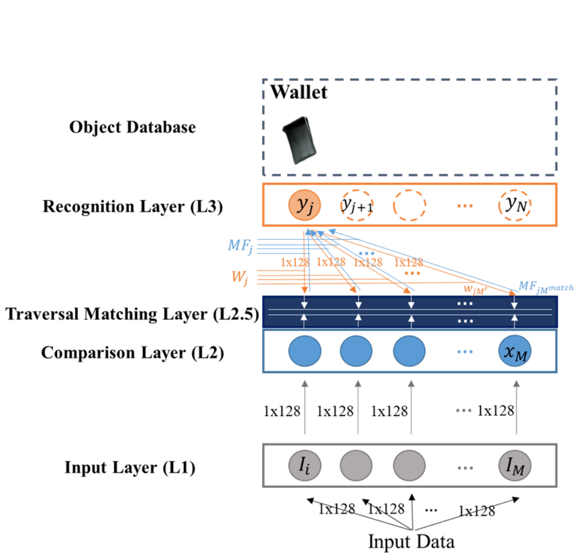

Fig. 2 Structure of our proposed SIFT-ART model

First, the feature points of the targets, like human face or object, can be derived from SIFT, and is presented as input data of SIFT-ART. As shown in (1), K feature points are obtained from an image by SIFT, and each feature point with a 128-dimensional descriptor, so it can be considered as a Kx128 input data. Then we assign these K feature points to k nodes respectively in L1 of our SIFT-ART model, that means each nodes only get one feature point with 128-dimensional descriptor.

$$I = \overbrace{\left[\underbrace{\begin{bmatrix} k_{1,1} \\ k_{1,2} \\ k_{1,3} \\ \vdots \\ k_{1,128} \end{bmatrix}}_{I_1}, \underbrace{\begin{bmatrix} k_{2,1} \\ k_{2,2} \\ k_{2,3} \\ \vdots \\ k_{2,128} \end{bmatrix}}_{I_2}, \underbrace{\begin{bmatrix} k_{3,1} \\ k_{3,2} \\ k_{3,3} \\ \vdots \\ k_{3,128} \end{bmatrix}}_{I_3}, \underbrace{\cdots}_{\cdots}, \underbrace{\begin{bmatrix} k_{K,1} \\ k_{K,2} \\ k_{K,3} \\ \vdots \\ k_{K,128} \end{bmatrix}}_{I_K} \right]}^{\text{K feature points}}, \quad (1)$$

where K is the numbers of feature points extracted by SIFT.

$$I_{nor} = \frac{I - \boldsymbol{min}(I)}{\boldsymbol{max}(I) - \boldsymbol{min}(I)} \quad (2)$$

Then, we normalize I by (2), and presented to Comparison Layer (L2) $X = [\boldsymbol{x_1}, \boldsymbol{x_2}, \boldsymbol{x_3}, \ldots, \boldsymbol{x_M}] = \boldsymbol{I_{nor}}$ by one node to one node.

By adding the new layer, Traversal Matching Layer (L2.5) as shown in Fig. 2, for each normalized feature point x_i, can be paired to the most similar features of the existing category y_j one by one, and same process is executed for each existing categories. Then the degree of similarity is calculated by Euclidean distance of x_i and each feature w_{ji} of the chosen category y_j. All of the above processes are shown in following formulas.

$$\begin{aligned}
&minDist(x_i, w_{jm'}) = \min\{E.D.(x_i, w_{jM_1}) | M_1 = 1,2,3,\ldots,M'\} \\
&secondminDist(x_i, w_{jm'}) = \min\{E.D.(x_i, w_{jM_2}) | M_2 = 1,2,3,\ldots,M' \cap M_2 \neq M_1\} \\
&T_j = avgDist_j = mean\left\{\textstyle\sum_{i=1}^{M} minDist(x_i, w_{jm'}) \,\middle|\, \frac{minDist(x_i, w_{jm'})}{secondminDist(x_i, w_{jm'})} < \gamma\right\} \\
&(M_1, M_2) = \{(x, y) | x = M_1 - m', y = M_2 - m'\} \text{ after getting } T_j \\
&T_J = min\{T_j | j = 1,2,3,\ldots,N\} \\
&\text{where } \gamma = 0.75 \text{, and E.D. is Euclidean Distance, i.e., } E.D.(A, B) = \\
&\sqrt{(a_1 - b_1)^2 + (a_2 - b_2)^2} \text{, where } A = (a_1\, b_2),\ B = (a_1\, b_2)
\end{aligned} \quad (3)$$

Only the categories with the lowest value from the result of choice function T_j become the candidate categories, which can be only one or more. Matched function MF_j, as shown in (4), then is executed to decide the best one category of all candidates for the input, the resonance of our SIFT-ART model occurs when match function meet the vigilance criterion $MF_j \geq \rho$, otherwise create the new category y_{j+1} for the input I.

$$MF_j = \frac{the\ number\ of\ matched\ keypoints}{the\ number\ of\ input\ keypoints} \quad (4)$$

Three possible results of our SIFT-ART model as shown in Fig. 3. i) Case 1: Input can directly be classified to one of the existing category, or becomes either case 2 or case 3. ii) Case 2: While the match function does not meet the vigilance criterion, then ask for user's preference. If there already exists the category as the same as user's preference, then update the features of the category by

$$\begin{aligned}
(w_{ji})^{new} &= (1 - \beta) * (w_{ji})^{old} + \beta * x_i, \quad i = 1,2,3,\ldots,M, \\
\beta &= \frac{\rho - MF_j}{\rho},
\end{aligned} \quad (5)$$

Also, the model incrementally enlarge the $(w_{JM})^{new}$ to $(w_{JM''})^{new}$, if $M'' > M$. For those features $(w_{Jk})^{new}$, $k = M + 1, M + 2, \ldots, M''$ are the same as the feature points in X without pairing.

Otherwise the situation can be considered as case 3. iii) Case 3: If there is no existing category as the same as user's preference than create a new category for the input by $(W_J)^{new} = X$.

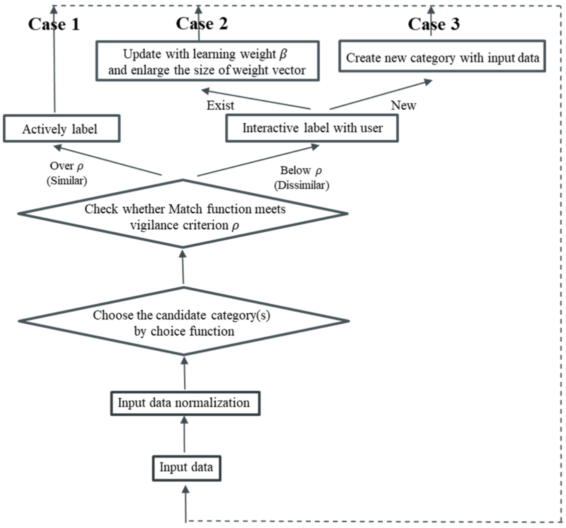

Fig. 3 Overall workflow of our proposed SIFT-ART model

- Frequent human-object-time association rule generation

After the processes of our SIFT-ART model, our system possesses the ability to recognize the human's faces and objects in the environment, and keeps incrementally updating and enhancing for both existing knowledge and new ones. For our case, in order to detect some deviations that beyond user's daily life, exploring the human-object-time association rules is a requisite.

A. Time-based sequential tree construction

Based on sequential pattern tree [9], we can efficiently store the event by their time order in a reduce storage space. Since people's habits are usually identified by everyday routines, time information plays a critical role. We separate the working hour of one day from 9:00 A.M to 8:59 P.M. to three time segments, i.e., Morning: 9:00 A.M.~12:59 P.M., Afternoon: 1:00 P.M.~4:59 P.M., and Evening: 5:00 P.M.~8:59P.M., each four hours for one time segment. Then three different tree roots are built to store the sequence events with different time segment information respectively

B. Pair-wised pattern extraction

After storing the events as the sequential tree based structure, each branch contains numbers of nodes, and each node with one event name, the count number, and the Event ID to this node, for the example from [9], event ['a': 4: 1], means that the count number is 4 and the Event ID is 1 for event 'a'. By traversing all branches to extract the pair-wised patterns with only two events in order, i.e., patterns ['d', 'c', 1] and ['c', 'a', 1] can be obtained with the count of the latter event for each pattern at the last element, if the sequence event ['d': 1: 1, 'c': 1: 2, 'a': 1: 3] is stored in one of the branches. Because we also include the characteristics of Event ID, those events with the same Event ID, in our case, means that events happen at almost same time, the pair-wised patterns sometimes contains more than two events when this pattern can extend itself to find the previous or latter events in the same branch with the same Event ID, i.e., patterns [('a', 'd'), 'c', 1] and ['c', ('a', 'e'), 1] can be obtained if the sequence event ['a': 4: 1, 'd': 1 :1, 'c': 1: 2, 'a': 1: 3, 'e': 1: 3] is stored in one of the branches. Then, for those patterns with same pair-wised events, keep only one of them and sum the counts among them, so we can get the streamlined patterns with the total count for each of them.

C. Association rule generation

From [10], Support-Confidence can be used to generate association rules between two events of each pair-wised patterns, the Support is the same calculation as [10] for our case, but for Confidence, we change it to

$$Confidence^*(X \rightarrow Y) = \frac{Support(X \rightarrow Y)}{Support^*(X)}, \quad (6)$$

where $Support^*(X)$ means that the percentage of those patterns containing the X event happens at first term in whole event pattern database.

Finally, according to the collected patterns, the association rules can be generated, and Confidence Correlation Table is built by summarizing all rules, an example is shown in Fig. 9.

Based on the Confidence Correlation Table, the degree of correlation for every two events, the former one and the latter one, are stored as confidence value form. For those event probably happen next can easily be predicted, on the other hand, the former events with the high confidence value can also be checked.

D. Association rule update

By the sequential pattern tree structure, the tree is extendable. After the confidence correlation table built from the first-day tree, for the second day the first-day tree can directly be incremented by second-day patterns, and depends on the new extended tree, new confidence correlation table can be obtained. Thus, the tree keeps growing up and new association rules can be explored as well.

- Fog computing structure

Fog computing [3, 4], performing data analytics, control, and other time-sensitive tasks close to end users, is the ideal and often the only option to meet the stringent timing requirements of many IoT systems.

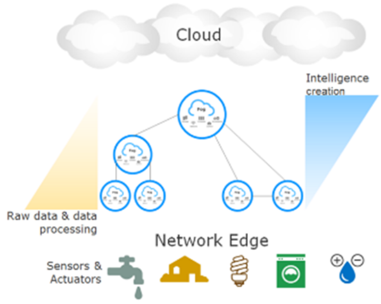

Fig. 4 Fog computing structure [4]

In our system, the analytics on continuous video data is core function. If we put all the computing tasks only on Cloud, which is always far from end users, then the data need to be transmitted through a farther distance to Cloud platform all the time, and then feedback the results to end side for services, for example, giving alerts when some anomalies happen. However, by the longer communication time directly to the cloud, the opportunity to act on data might be gone. For another case, if we assign all the computing tasks only on end device, which can save the communication latency, but the limited computing resources on end device need much more extra computation latency. Hence, we involve Fog computing structure in our proposed architecture shown in Fig. 5. By separating all functions into three sub-parts, the first one is video data collection in device layer, the second one is human-interactive and incremental human/object recognition and deviation detection in Fog Layer, which analyzing data close to end users instead of sending vast amount of raw video data to the Cloud, and the third part is frequent sequential human-object-time association rule generation in Cloud Layer. Only the valuable data instead of all the raw video will be sent to the cloud for long-term analysis and storage, then the rules for deviation detection can be updated. By Fog computing, we can significantly reduce the communication latency and get the shortest computation latency at the meantime. Fig. 5 shows the conceptual structure of Fog computing that support to our proposed human-interactive intelligent monitoring system, and based on the structure, the implementation of our system architecture is shown in Fig. 1.

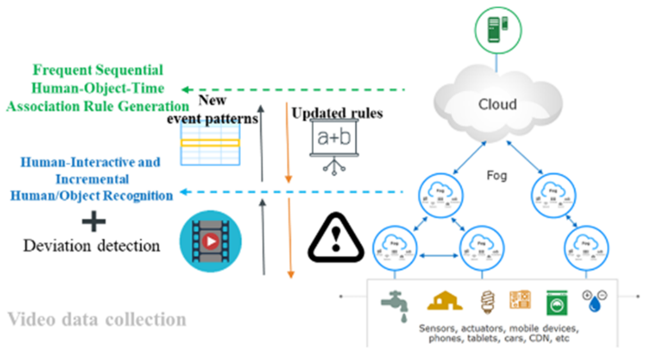

Fig. 5 Conceptual Fog computing structure of our application

IV. Experiment Results

The following experiments are all implemented in our laboratory environment for 10 days. In such a semi-open space and cubicle based lab environment, the more intelligent way for monitoring is necessary.

For scenario 1, the system can be everyone's smart reminder, depends on the rules, it can know something that user forgot to do. For instance, the user always carry on his/her back bag without leaving any personal belongings on the desk only before leaving, one day when back bag is taken away but something still left on desk, then give a warning in time. For scenario 2, it can also be the smart anti-theft system, the rules can also be used to check whether there is a stranger close to the user's seat and something is taken by the stranger at some time. Fig. 6 shows the examples of the above 2 scenarios with two cameras.

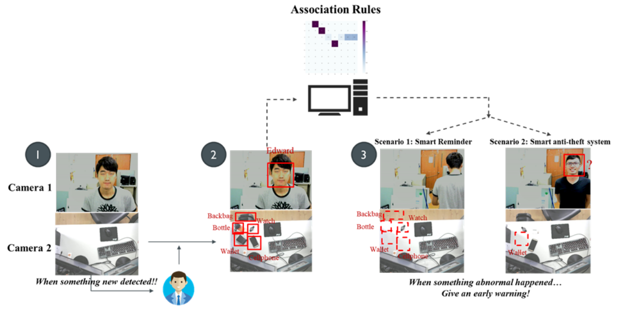

Fig. 6 Experiment scenarios in our lab environment

The followings are experimental results for human-interactive and incremental human/object recognition on Fog node, human-object-time association rule generation on Cloud, and deviation detection on Fog node according to the rules generated from Cloud are illustrated respectively. Finally, the latency reduction by fog computing structure are elaborated as well.

When there is a new input target detected and presented to our model, then the following online testing and offline testing will be executed one time, and the counter of executions in the following line graphs is increased by 1.

For online testing, the image is learnt by our SIFT-ART model, and the result will be one of the following three cases. i) Our SIFT-ART model can automatically make the right classification, which is represented as a dot (•). ii) Sometimes our SIFT-ART model cannot make decision by itself, it is necessary to ask for user's preference, which is represented as a filled triangle (▲). iii) Our SIFT-ART model make wrong classification by itself, which is represented as a cross (×) in below line graphs.

For offline testing, each time after online testing, in order to know how smart our SIFT-ART model is, we check the error rate by presenting 100 images of the person (Ex. Edward), which are collected in advance, to model to see how many images cannot be classified excluding any learning processes.

After adjusting value of ρ {0.3, 0.4, 0.5, 0.6}, we realized that when setting higher ρ, the error rate is declined slowly, the model is more sensitive to the variation of input, and the times of asking for user's knowledge is raised obviously, while the lower value of ρ, though not only the asking times is reduced but also the error rate can be sharply dropped in first few executions, the case of self-misclassification begins to happen due to the low strictness of similarity criterion.

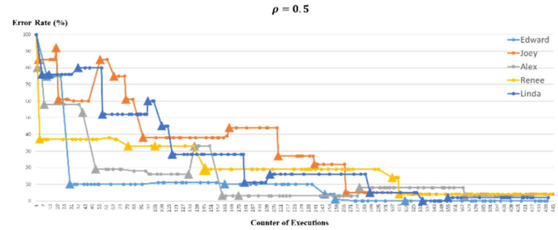

Fig. 7 Experiment results with setting $\rho = 0.5$ on human recognition

Table. 1 Statistics table of the results on human recognition

	Edward	Joey	Alex	Renee	Linda
Total apperance times	80	100	83	84	97
Overall asking times (online testing)	6	11	10	6	12
Overall asking times/Total appearance times	0.11	0.09	0.08	0.11	0.07
Overall self-misclassification times (online testing)	0	0	0	0	0
Overall self-misclassification times/Total appearance times	0	0	0	0	0
Final error rate (offline testing)	0	0.04	0.03	0.04	0.02

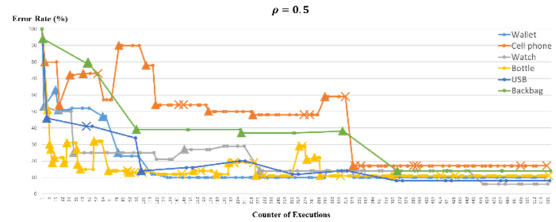

Fig. 8 Experiment results with setting $\rho = 0.5$ on object recognition

Table. 2 Statistics table of the results on object recognition

	Wallet	Cell phone	Watch	Bottle	USB	Backbag
Total apperance times	76	102	60	250	20	20
Overall asking times (online testing)	5	11	4	22	2	7
Overall asking times/Total appearance times	0.066	0.11	0.067	0.088	0.1	0.35
Overall self-misclassification times (online testing)	0	12	0	17	1	0
Overall self-misclassification times/Total appearance times	0	0.12	0	0.068	0.05	0
Final error rate (offline testing)	0.1	0.17	0.06	0.11	0.08	0.14

The results of setting ρ=0.5 are shown in Fig. 7 and 8, which indicate that our SIFT-ART model can learn new targets, which are human's faces and personal belongings in our case, at any time without forgetting the existing ones, and can automatically make decisions while the targets have already learnt before. Also, the error rate from offline testing is declined after observations for few times.

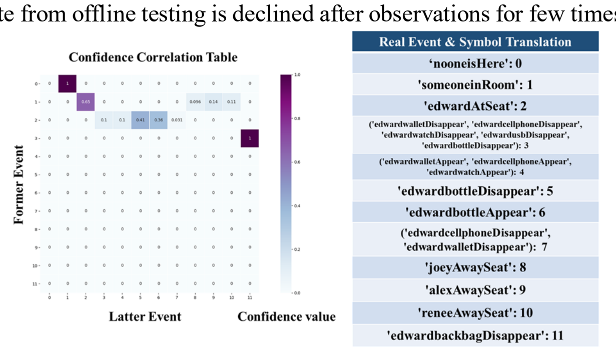

Fig. 9 Human-object-time association rules of evening time segment

After recognition results from our SIFT-ART model, Fig. 9 shows all frequent sequential human-object-time association rules generated from the event patterns after experiment for 10 days. Since our SIFT-ART model is expandable for recognizing new targets, the new potential association rules can also be explored day by day, then be added to the existing confidence correlation table.

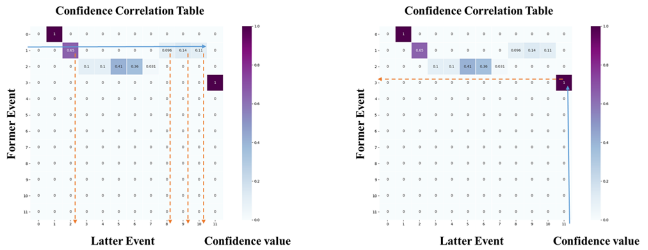

Fig. 10 Deviation detection by confidence correlation table

According to the Fig. 10, along with the row side by forward checking, as shown in the left table, the latter event with the highest confidence value can be expected happen next, which is for prediction purpose. On the other hand, along with the column side by backward checking, as shown in the right table, the former abnormal event can also be detected, which is for reminder purpose.

The following two structures are used for latency comparison.

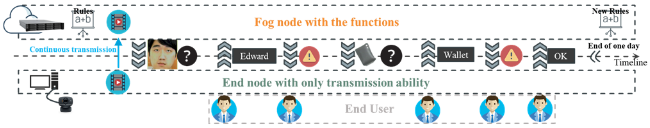

Fig. 11 Structure I

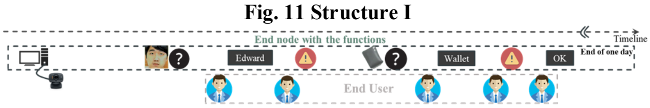

Fig. 12 Structure II

Table. 3 Latency on each part of two structures

Latency(second)	Structure I	Structure II	Disparity (I-II)
Frame Transmission(E->F)	0.1753098	X	0.1753098
Face Recognition	**0.0386498**	0.03875	-0.0001002
Face Frame Transmission(F->E)	0.0075685	X	0.0075685
Face Name Transmission(E->F)	0.0014143	X	0.0014143
Deviation Detection	**0.00049**	0.005	-0.00451
Object Recognition	**0.5131586**	1.018382	-0.5052234
Object Frame Transmission(F->E)	0.0056376	X	0.0056376
Object Name Transmission(E->F)	0.00152645	X	0.00152645
Deviation Detection	**0.0000773**	0.00402	-0.0039427
Event Approval Word Transmission(F->E)	0.000152	X	0.000152
Total	**0.74398435**	**1.066152**	**-0.32216765**

Table. 4 Composition of computation and communication latency (E: End node, F: Fog node)

Computation Latency	Face Recognition+Deviation Detection+Object Recognition+Deviation Detection
Communication Latency	Frame Transmission(E->F)+Face Frame Transmission(F->E) +Face Name Transmission(E->F)+Object Frame Transmission(F->E) +Object Name Transmission(E->F)+Event Approval Transmission(F->E)

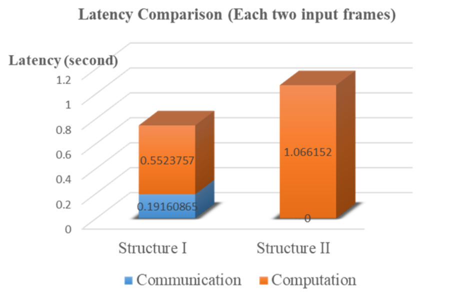

Fig. 13 Latency comparison on each two input frames

In order to validate the latency reduction on fog computing structure, we use two structures to do the same experiment as shown in Fig. 11 and 12 respectively. For structure 1 we assign time-sensitive part, human-interactive and incremental recognition part and deviation detection part to fog node, and end node only has transmission ability, while assign both parts on end node in structure 2 without transmission. Table. 3 summarizes the latency cost on each part of the experiment. Table. 4 summarizes all parts into two main kind of latency type, communication latency and computation latency. Fig 13 shows the total disparity of latency cost on analysis for each frame. In structure 1, though the communication latency is necessary, the computation latency is reduced more considerably.

V. Conclusion

In this paper, we propose a Fog-based human-interactive intelligent monitoring system which can keep updating or creating its knowledge according to user's preferences and its observation, not only for recognition on human and objects but also the human-object-time association rule generation, so some of the implicit values can be explored for assisting user in more customizable and precise way. Fog computing structure is involved to support our system to give user real time response while some anomalies happen. By separating all computing tasks to Cloud, Fog, and end node respectively, leveraging their computing capabilities, provide the real-time responses.

In the future, by the optimization of our SIFT-ART human-interactive learning processes and scaling up our system with the cooperation of Fog nodes, it can deal with some other applications, like elderly care or industry automation, with only very few human efforts or even without human's efforts anymore.

VI. Appendix

The spec of our Fog node and end node are shown in Table. 5 and 6 respectively.

Table. 5 Spec of our Fog node (left) and end node (right)

CPU	Intel Xeon E5-2680v4
Core #	14
Threads #	28
Processor Base Frequency	2.40 GHz
Max Turbo Frequency	3.30 GHz
Cache	35MB smartCache
Bus Speed	9.6 GT/s QPI
# of QPI Links	2
TDP	120W
VID Voltage Range	0

CPU	Intel Core i7-7700
Core #	4
Threads #	8
Processor Base Frequency	3.60 GHz
Max Turbo Frequency	4.20 GHz
Cache	8MB smartCache
Bus Speed	8 GT/s QPI
# of QPI Links	0
TDP	65W

Table. 6 Spec of our network condition

	Fog Node	End Node
Upload (Mbps)	62.978	12.092
Download (Mbps)	95.6431	97.6744

VII. References

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