Using Pattern Recognition and Internet of Things to Improve Energy Recovery Ventilation.

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Abstract— **Indoor air quality has been paid more attention gradually. Many countries begin to build standards to examine the environmental factors around human's lives. However, they spend most of their time on indoor activities, especially being in a large number of spaces. It is more likely to cause the dramatic increase in CO_2 concentration. In order to reduce the indoor harmful substances, Energy Recovery Ventilation is usually set up for indoor and outdoor air exchange. Nevertheless, the Energy Recovery Ventilation cannot be used more effectively, and it increases the use of unnecessary energy. Therefore, there is a proposal related to pattern recognition which combined with sensor modules to control the time of using Energy Recovery Ventilation. As a result, the space meets the requirements of CO_2 concentration, and there is a classroom with Energy Recovery Ventilation as the testing object in our experiment. Also, the result shows that the system can effectively decrease the indoor CO_2 concentration under the control of Energy Recovery Ventilation switch. The concentration does not overstep the standard and provides users with a comfortable environment as well.**

I. Introduction

With the rapid development of industry and urbanization, ventilation is one of the best methods to improve indoor air quality (IAQ). The assessment of IAQ factors include carbon monoxide (CO), carbon dioxide (CO_2), methane (CH4), particulate matter (PM) and volatile organic compounds (VOCs), These factors will not be significantly improved under normal use except carbon dioxide. It increases along with time, especially in a confined space and environment with high human density. For instance, when carbon dioxide in the space exceeds 1000 ppm, users feel uncomfortable and their concentration decreases (Gall et al., 2016; Satish et al., 2012; Shriram et al., 2019; Zhang et al., 2017). However, the American Society of Refrigeration and Air Conditioning has different air exchange regulations for different spaces, such as 17 CFM / person and 8 CFM / person for classrooms and lecture halls (ASHRAE, 2013).

With the development of Internet of things technology, it is very easy to collect and obtain data. In previous studies, the observation of indoor air quality is also the point of most scholars. For example, Zhao et al. (2019) used multiple communication interfaces to connect different sensors, which meets the needs of different sites. In the clients' point of view, the user sensor can be added or deleted by modularization (Benammar et al., 2018). However, the application of Internet of things is no longer the data collection and storage in the front end. In the current days, the main problem is how to analyze and use a large amount of data. In the application of indoor air quality data, the problem of high indoor carbon dioxide concentration is solved by combining artificial neural networks and Internet of things (Tagliabue et al., 2021). With the more space capacity, the rising speed of carbon dioxide concentration is relatively increased. Therefore, the way to forecast the number of users in the space is to measure carbon dioxide concentration and make use of machine learning. (Candanedo & Feldheim, 2016; Fraga-Lamas et al., 2019).

The combination of machine learning and Internet of things has achieved considerable research results in most fields, such as UAV obstacle detection and collision avoidance (Fraga-Lamas et al., 2019), analysis of the development of smart city (Atitallah et al., 2020) and indoor comfort (Valladares et al., 2019). In terms of indoor monitoring, Candanedo and Feldheim (2016) used linear discriminant analysis (LDA), classification and regression trees (CART) and random forest (RF) models to predict the temperature, humidity and CO_2 in the office. The result was 95% - 99%. To test the indoor air quality, he et al. (2017) also compared four ways including BP, support vector machine (SVM), radial basis function (RBF) and learning vector quantification (LVQ). Finally, BP neural network had the best predictive effect.

In order to improve the switching time of the Energy Recovery Ventilation, this study combines the methods of carbon dioxide concentration detection and pattern recognition to make sense of the changes of personnel density and carbon dioxide concentration in the actual field. In addition, this study provides the Energy Recovery Ventilation with an appropriate time for power switch, leads the CO_2 concentration in the space to the standard range and, above all, offers users a comfortable environment.

II. Faster R-CNN

As early as the 19th century, there have been relevant researches. Until the rapid development of modern computer hardware, the application and technology of pattern recognition have become riper. It is common for us to solve the problems of computational quantity (Reza et al., 2017),and quality (Liang et al., 2019) and object classification as well(Kulkarni et al., 2018). R-CNN, Fast R-CNN, Faster R-CNN, Mask R-CNN, YOLO models have been developed in the object detection method. However, real-time object detection of faster R-CNN is widely used by everyone (Ren et al., 2015). Figure 1 shows the overall architecture of faster R-CNN.

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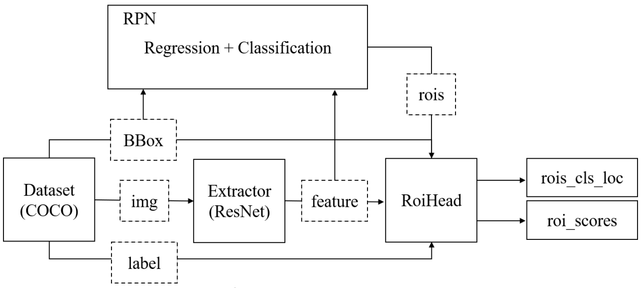

Figure 1. Faster R-CNN

III. Method

This research method is mainly divided into sensor measures and pattern recognition. It collects the environmental data and the number of observers respectively. After collecting the data, it is sent back to the database, and then it is communicated to the ERV by the control terminal operation. The steps are mainly divided into four steps: set environmental factors, data collection, save data and data communication.

Step 1. At present, most of the environmental data can be collected by sensors in the market. It must be confirmed to collect useful information under the budget. In the calculation of the numbers of observers, the pattern recognition method is fast and can reduce unnecessary human resources.

Step 2. In this study, environment information collected CO_2, temperature and humidity, and combined with Arduino Yún, Base Shield and Grove - SCD30 collects and transmits data. Number of observers calculates the number of observers in space through python, OpenCV and coco dataset.

Step 3. The MySQL database is used as a data storage sensor and identification module, resulting in temperature, humidity, CO_2 and number of observers.

Step 4. After grabbing the database data, when the CO_2 concentration reaches 800 ppm, the ERV is turned on, and the number of observers mainly calculates the quantities of fresh air that the ERV needs to input. Besides, the operation is stopped after inputting the appropriate air.

According to this method, the ERV can be effectively controlled, the opening and closing time of the ERV can be more efficient, and the relationship between humans and the environment can be combined. Thus, the ERV can take into account human rather than only environmental factors in energy saving.

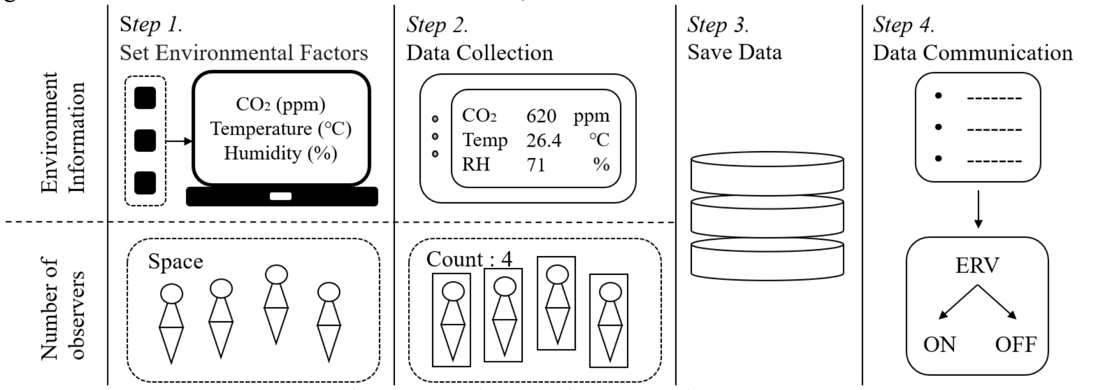

Figure 2. Control ERV ON/OFF proposed system

IV. The Experiment

In this section, we will briefly introduce an overview of the case presented, and then discuss the experimental results.

A. The Proposed Case

The experimental site is a classroom in the university and the doors and windows in the classroom are closed. The ventilation is only done by ERV. The number of people in the space is 31. The ERV is ALASKA (VH-63158), and the air volume is set to 1500 m^3/h, as shown in Figure3. Sensor models and camera installation location as shown in Figure 4.

Figure 3. ERV diagrammatic sketch

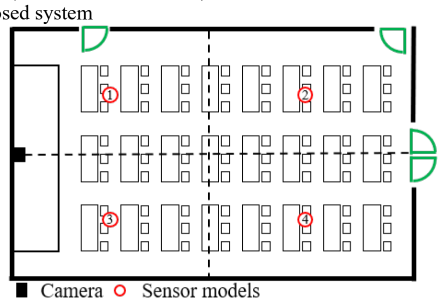

Figure 4. Sensor models and camera installation location

B. The Experimental Results

The experimental results prove that in Table 1 and Figure 4. CO_2 concentration in the operation of the system did not exceed the predetermined value of 1000 ppm, and the highest value is 862 ppm (11:27). Moreover, ERV opening time is about 11:21, closing time is about 11:44, the total operation period is 23 minutes, and fresh air increased by about 575 m^3. Otherwise, the number of image identification measured before starting 20 people, which is shown in Figure 5 and calculated to be an inlet air volume of 577 m^3/h (17 CFM × 20 ×1.698) , as such, is similar to the actual version.

TABLE I. THE CO_2, TEMPERATURE AND HUMIDITY IN THE PROPOSED CASE

Times	CO_2 (ppm)					Temp. (°C)	Hum. (%)
	1	2	3	4	Avg.		
10:08	673	658	687	661	670	23.6	60
10:09	669	625	644	623	640	23.4	62
10:10	595	579	613	562	587	23.2	62
10:11	576	563	591	551	570	23	63
10:12	565	544	570	551	557	22.9	64
10:13	559	520	568	537	546	22.8	65
10:14	561	522	554	530	542	22.8	65
10:15	556	528	563	537	546	22.7	65
10:16	557	528	553	514	538	22.7	66
10:17	551	521	551	520	536	22.7	66
10:18	552	519	552	534	539	22.7	66
10:19	548	527	543	522	535	22.7	66
10:20	548	526	561	513	537	22.7	66
10:21	553	500	552	509	528	22.7	66
10:22	537	504	541	510	523	22.7	66
10:23	543	513	556	511	531	22.6	66
10:24	538	529	554	512	533	22.6	66
10:25	552	520	537	509	529	22.5	66
10:26	545	535	541	513	534	22.4	67
10:27	550	529	553	521	539	22.3	67
10:28	564	528	553	515	540	22.3	67
10:29	557	504	536	527	531	22.3	67
10:30	568	533	564	518	546	22.3	67
10:31	555	523	541	527	536	22.2	67
10:32	540	524	532	520	529	22.2	67
10:33	571	536	564	533	551	22.2	67
10:34	601	568	609	579	589	22.2	67
10:35	550	539	551	516	539	22.2	67
10:36	583	543	564	526	554	22.2	67
10:37	569	521	552	529	543	22.2	67
10:38	577	548	560	538	556	22.2	67
10:39	563	544	568	545	555	22.2	67
10:40	574	544	570	544	558	22.1	67
10:41	577	546	558	524	551	22.1	67
10:42	592	546	578	536	563	22.1	67
10:43	584	572	600	554	577	22.1	67
10:44	606	552	583	563	576	22.1	67
10:45	586	562	580	574	576	22.2	67
10:46	571	554	579	553	564	22.2	67
10:47	587	548	582	565	571	22.3	66
10:48	590	547	595	547	570	22.3	66
10:49	598	572	579	565	578	22.3	66
10:50	609	574	591	566	585	22.3	66
10:51	603	568	589	560	580	22.2	66
10:52	614	568	616	576	593	22.3	66
10:53	609	574	592	565	585	22.2	66
10:54	596	589	615	583	596	22.2	66
10:55	602	556	597	585	585	22.2	66
10:56	614	581	614	561	592	22.2	66
10:57	614	574	607	577	593	22.2	66
10:58	610	580	606	590	596	22.2	66
10:59	625	576	615	590	601	22.1	67
11:00	620	572	608	567	592	22.1	67
11:01	613	588	610	589	600	22.1	67
11:02	614	576	616	598	601	22	67
11:03	603	588	615	590	599	21.9	67
11:04	638	609	618	590	614	21.8	67
11:05	661	617	658	609	636	21.8	68
11:06	655	623	657	618	638	21.8	68
11:07	662	632	664	641	650	21.9	68
11:08	665	639	659	648	653	21.9	68
11:09	671	621	662	621	644	21.9	68
11:10	681	638	664	650	658	22	68
11:11	686	647	677	644	664	22	68
11:12	677	659	691	644	668	22.1	67
11:13	681	655	694	668	674	22.1	67
11:14	695	662	692	651	675	22.1	67
11:15	703	698	728	673	701	22.1	67
11:16	743	726	747	735	738	22.2	67
11:17	772	745	766	738	755	22.2	67
11:18	789	751	787	748	768	22.2	67
11:19	789	773	800	760	781	22	67
11:20	802	767	801	774	786	22	67
11:21	813	794	805	791	801	22	68
11:22	830	794	816	790	807	22	68
11:23	828	811	831	799	817	22	68
11:24	855	804	845	807	828	22	68
11:25	860	824	866	826	844	22.1	68
11:26	857	838	856	829	845	22.1	68
11:27	872	844	878	854	862	22.1	68
11:28	868	836	858	837	850	22.2	67
11:29	828	807	830	802	817	22.2	67
11:30	833	779	813	791	804	22.2	67
11:31	820	792	810	783	801	22.3	67
11:32	771	744	799	748	766	22.3	66
11:33	745	733	763	740	745	22.3	66
11:34	759	715	758	715	737	22.3	66
11:35	742	722	734	724	730	22.4	66
11:36	750	701	746	717	729	22.4	66
11:37	740	716	745	719	730	22.4	66
11:38	744	694	718	685	710	22.4	65
11:39	715	695	712	700	706	22.5	65
11:40	711	703	739	707	715	22.5	65
11:41	724	679	732	693	707	22.5	65
11:42	710	687	706	680	696	22.5	65
11:43	684	654	677	655	668	22.6	64
11:44	683	655	684	647	667	22.6	64
11:45	680	641	668	649	659	22.6	64
11:46	669	657	665	630	655	22.6	64
11:47	688	650	661	658	664	22.7	64
11:48	659	653	667	655	659	22.7	64
11:49	682	649	678	625	658	22.7	63
11:50	663	641	657	650	653	22.8	63
11:51	675	641	653	628	649	22.8	63
11:52	671	629	664	630	648	22.8	63
11:53	672	646	654	637	652	22.8	63
11:54	655	640	671	621	647	22.9	62
11:55	656	636	643	626	640	22.9	62
11:56	661	630	647	625	641	22.9	62

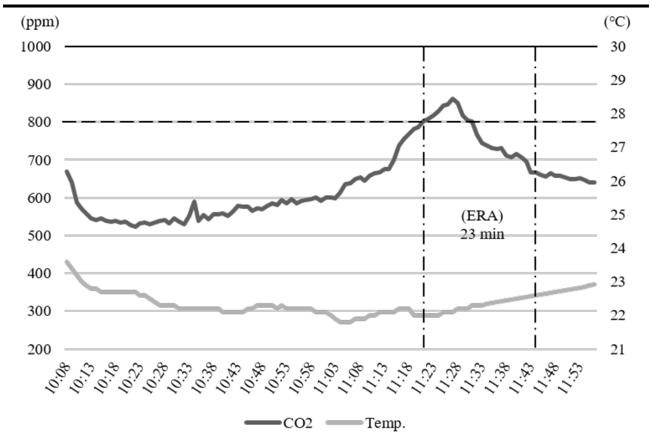

Figure 4. The trend of experimental results (CO_2 & Temperature)

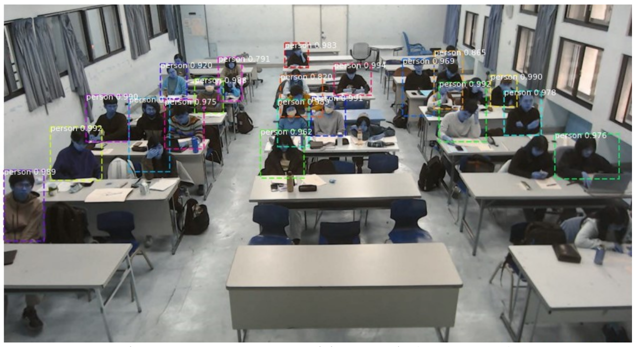

Figure 5. Pattern recognition result (20 persons)

This research method has been verified in the actual classroom, through the effective control of era, it is feasible to reduce the indoor CO_2 concentration, and the concentration can be maintained within the standard value. Even though some students came in and out of the classroom during the experiment, the results show few changes of CO_2 concentration. Because the CO_2 concentration was not evenly distributed in space, especially after the average of four sensor models, the difference between CO_2 concentrations was reduced.

V. Conclusion

There are currently only on and off buttons in the ERV system. The unconsidered inlet air leads the ERV system which is in the original set value to be closed. But, the close indoor and outdoor concentration still do not reach the predetermined closing value and ERV is still running. This study has been proved by experiments and this feasible method. The indoor CO_2 concentration can effectively reduce and be less than 1000 ppm by means of the quantitative inlet air provision. Finally, in order to improve the accuracy of identification, it is suggested to train a suitable model in pattern recognition.

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