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ABSTRACT

In building energy calculation, several energy fluxes can be associated to occupants interacting with building services such as light or HVAC system switching on/off, the thermostat settings as well as window and shading operation. These interactions - always caused by discomfort - are undertaken to restore comfort but can have consequences on the final energy demand. Thus, an accurate building energy simulation for both new and retrofit building design needs to correctly represent people's behavior.

In this paper, a new measurement approach has been developed to collect information about the window's opening angle and shading position, both measured continuously along time. To achieve this, a camera setup connected to a Raspberry Pi microprocessor is designed to track window movements through a color recognition algorithm coded in Matlab. The examined windows and shadings are color coded on the moving parts with rectangular targets. The camera is equipped with wide angle lenses and a physical barrier to be able to capture all present windows and shading simultaneously while ensuring the privacy of occupants.

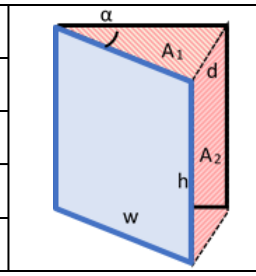
Preliminary results show that the proposed monitoring system can monitor window opening angles and shading levels, dealing simultaneously with multiple windows. The validation of the method will allow to develop accurate behavioral models based on the obtained data to analyze and suggest improvements for the indoor air quality of classrooms. Moreover, the output data from this equipment can be used to model the window opening free area and perform calculation on the ventilation rate according to EN 16798-7.

1. INTRODUCTION

The detailed understanding of occupant behavior plays a key role towards the improvement of performance estimation and comfort in energy efficient buildings (O'Brien et al., 2020). Especially in environments gathering many people and being solely naturally ventilated by windows and doors, the profound understanding and development of effective ventilation strategies is of major importance. The opening of windows significantly influences the thermal exchange between in- and outside environment. The European standard EN 16798-7:2017 (EN, 2018) deals with the calculation methods for the ventilation of buildings. The amount of airflow through a window depends on the window open area, next to wind speed and direction, turbulence conditions, and the internal-external temperature difference (Coley, 2008). The window open area is given by the product of widow size and opening fraction which can be calculated using the opening angle. As shown in Table 1, opening angles around 20° already represent an opening fraction of around 50%. Therefore, for detailed analysis and in depth understanding the aperture angle α plays an important role as it affects the flow rate depending on the window opening area. According to EN 16798-7:2017 (EN, 2018), the air flow entering through window opening is directly proportional to this area.

Table 1: Opening angle α, opening distance d, window open area A & open fraction.

α [°]	**d [m]**	**A [m²]**	**Open fraction [%]**
5	0.087	0.262	13
10	0.174	0.522	26
15	0.261	0.781	39
20	0.347	1.037	52



* e.g., for a window of h = 2 m and w = 1 m, calculated according to (Coley, 2008)

Furthermore, the area of the totally opened window is affected by the use of shadings as they cover a big part of the window. For accurate calculation of the natural ventilation provided by the opening of windows it is therefore essential to have information about the windows opening angle and shading position. Consequently, a detailed monitoring approach of window opening angles, shading positions and lights is proposed in the here presented research proceeding.

1.1 Comparison of already existing technologies to monitor window opening

Regarding the prediction of windows and shading operation, in literature a few models have been developed to predict the window opening angle and the shading factor according to indoor or outdoor conditions. These models are usually calibrated and validated using experimental data collected by means of accelerometers, contact sensors, Bluetooth devices, ultrasound, or laser sensors, which are used to calculate the changes of the magnitude of the net exchange surface area with increasing window opening angle and obstacles such as shadings covering a portion of the opening. Almost all these devices have two drawbacks: i. they return binary outputs or ii. they have possible information losses related to a limited working distance, viewing angle or spatial resolution.

Therefore, most research proceedings due to simplicity only consider the binary status of building services such as lights, windows, and shadings. Only a few studies (Fritsch et al., 1990; Haldi & Robinson, 2009) within the here analyzed literature consider the measurement of window opening angles. The main reasons for the underestimation of the value of angle measurements are either that the research interest is purely phenomenological or the avoidance of the experimental effort to measure the angles. The most common monitoring approaches are:

1.1.1 Contact Sensors: Sensors which close an electric circuit on contact are commonly used in most monitoring campaigns (e.g., Park & Choi, 2019). They are a cheap solution, but some disadvantages include their quite complicated wiring for each window and the binary output. Therefore, windows are assumed to be fully opened even if they are just slightly opened at only 10°.

1.1.2 Air speed measurements: Stazi et al. performed in 2017 a campaign to improve indoor air quality and comfort in classrooms using automated systems such as Pitot tubes to measure the air stream entering a window. This allows for a direct monitoring of the ventilation rate as it includes already the windows aperture and external parameters as in- and outdoor temperature difference and wind speed. However, the devices reading the pressure difference of a Pitot tube are quite expensive and it has the further disadvantage of just being able to monitor a single window.

1.1.3 Distance sensors using Bluetooth: Bluetooth sensors have been used to track the position of a certain target in a room (Clark et al., 2018). These sensors have the advantage of being quite cheap and already included in many devices such as cellphones. However, the accuracy is limited to 30 cm which excludes the use for window opening monitoring. A more suitable application would be presence monitoring.

1.1.4 Distance sensor using ultrasounds: Distance measurement using ultrasounds is a very accurate and at the same time cheap solution to measure a distance. To reflect sound correctly, the target must be perpendicular to the emitting source. This cannot be guaranteed on a rotating surface like a window that swivels around its axis.

1.1.5 Distance sensor using laser: The requirement that the surfaces must be at right angles to each other is not given here, making laser measurements an interesting technology to measure the opening of a window. However, the wiring is very annoying because il would be necessary to lay a separate cable to each window.

1.2 Possible advantages of using a camera

To minimize the effort to monitor all present windows at once and simultaneously maximize accuracy, a camera setup is being developed within the here presented work. The main feature is the possibility to recognize predefined colored targets mounted on the windows moving parts. Therefore, it is a valid alternative to the mentioned conventional methods of measuring window opening behavior which, to the authors knowledge, has not been fully explored in literature. Especially, the simultaneous non-intrusive monitoring of multiple windows, shadings, and lights at once without being much effort to mount, makes the presented device a promising alternative to conventional sensors. Combining the camera with a Raspberry Pi allows for data storage and post processing with the advantage to attach additional sensors and instrumentation if needed. A Wi-Fi port simplifies data extraction and small physical dimensions enhance the ease of installation. The development of this camera-based tool contributes to a large-scale monitoring campaign in Morlupo (Rome), aiming to fully understand the phenomena of IEQ in schools, the interactions of teachers and students with building services, and the effects that safety measures regarding viral loads have on performance, comfort, and behavior. The here presented monitoring device increases the level of detail of the monitored behavior using simple and affordable technology. The obtained data can be cross validated with alternative forms of data acquisition such as questionnaires and event checklists filled out by the students.

The general research aim therefore is to develop a versatile, not complex instrumentation to monitor in detail the main building services operated by occupants, namely windows, shadings, and lights in a continuous, nonbinary way. Further it has been a target to validate the device and explore possible additional applications of a camera-based tool, such as presence monitoring or desk illuminance. Further applications of a camera-based tool for indoor monitoring can be a occupancy count to improve management and control of ambient light, air flow and temperature as described in Alishahi et al. (2022). Luminance measurements (Kim & Tzempelikos, 2022) and forehead temperature measurements to estimate people's comfort (Speak et al., 2021) are of further interesting applications for indoor monitoring using a camera. A dynamic response to each condition could be provided by a optimal real-time monitoring control using a camera for the aforementioned applications.

2. METHODOLOGY

The study is based on three steps: the choice of suitable hardware components for the proposed monitoring device, the development of a reliable post-processing algorithm to convert the acquired images into processable data and finally the validation of the device using a sample dataset.

In the first development stage, the device will require some simple calibration to the properties of the monitored room. First, sample images showing each window fully open and closed need to be taken to determine the coordinates of the targets on the sensor's pixel pane when closed and fully open. In a next step five sample images of each possible light condition are required to define the according RGB-ranges of the red targets (windows), yellow targets (shades) and lights (white). Finally, an image cut-out area for the given room properties needs to be defined ensuring full visibility of the target's trajectory.

2.1 Technical Hardware

Regarding the hardware setup, the main components are a Raspberry Pi 4B with 8 GB Ram used as the data acquisition and handling unit as well as a high-definition camera and lens.

The newest model version of the Raspberry Pi is chosen because of its powerful working memory and processor unit. Further, it comes with Wi-Fi for remote data download. It has its own camera port and additionally a standard 40 pin general-purpose input/output (GPIO) board which allows for a simultaneous use of multiple sensors. For the present study a camera and a magnetic switch is connected to the Raspberry. The key components of the setup are the image sensor and camera lens. To choose adequately the lens aperture angle, room dimensions and sensor size must be considered carefully as the ability to successfully postprocess the images strongly depend on this parameter. Two different setups are considered for operation: (i) the standard Raspberry Pi camera model with an electrical board featuring a unit with image sensor and lens in one component, and (ii) the in Pi high quality image sensor recently released in 2020 which has a C/CS mount for interchangeable camera lens and tripod mount.

Given the larger horizontal field of view and the larger target resolution, setup 2 has the clear advantages of being able to monitor more windows simultaneously; it is more suitable for the classroom size in Morlupo and features a better target resolution. Many reviewers consider the 12.3 megapixel sensor as a noticeable upgrade providing sharper images and capturing more color (Medellin, 2020).

Table 2: Comparison of chosen Raspberry Pi Setups

Specification	**Setup 1: Raspberry Pi standard camera with integrated lens**	**Setup 2: Raspberry Pi HQ camera with 6mm wide angle lens**
Lens	Built-in	Raspberry 6 mm wide angle
Sensor	OmniVision OV5647	Sony IMX477
Sensor resolution [pixel]	2592 x 1944	4056 x 3040
Sensor image area [mm]	3.76 x 2.74	6.287 x 4.712
Horiz. field of view [°]	53.50 +/- 0.13	65°
Horiz. field of view* [m]	3.98 m	5,09 m
Target resolution* [pixel]	~ 15x42	~ 18x56
Cost [€]	118.65	202.16

* Assuming a camera to wall distance of 4 m and target size of 30 mm x 70 mm

The target size is chosen to be 30 mm x 70 mm for two main reasons: on the one hand, because the area is ensuring good visibility even if geometrically deformed if window swivels towards larger opening angles. On the other hand, the pixel resolution is sufficient to recognize target ratio and size accurately. The physical accuracy limits for angle measurements are given by the horizontal distance travelled depending on the opening angle and pixel resolution. Every error added is caused by inaccuracies during post-processing. Summing up, results need to be evaluated separately for *theoretical accuracy* connected to hardware components like maximum sensor resolution, target size and room geometry. And second, the limitations connected to the accuracy of the algorithm resulting in the *measured accuracy*.

Figure 1: Camera perspective on classroom (left); Camera & Raspberry Pi setup (right)

The tripod mount is used to attach the camera including the raspberry case to a DIN-rail mounted on the classrooms wall. A cable is run to the magnetic switch mounted on the classrooms door and connected to the Pi's GPIO board. The camera data and power cable are plugged into the raspberry camera port. Finally, the physical spacer between camera lens and sensor needs to be removed to ensure the focal length is suitable for indoor applications and shorter distances. The raspberry is run using the most recent release of the operating system Debian Linux 11 – codenamed Bullseye. Several internal files need to be adapted such as the file containing the network interface information to ensure functionality also in headless mode. Special attention needs to be given to protected institutional Wi-Fi ports referred to as EAP-Typ (Extensible Authentication Protocol). To access the Pi remotely, a VNC server needs to be installed and activated. For automated image acquisition and door sensor readings, two python scripts - *DoorLog.py & TakeImage.py* - are coded. They are embedded in Shell scripts automatically executed by a raspberry built-in functionality called *crontab* which schedules command execution. The main feature of the shell script is that it immediately names the images according to date and time. Finally, the graphical output of the raspberry is set to “experimental direct capture mode” to be able to view the camera preview image over the VNC connection. Otherwise not all video layers of the Pi’s graphical interface are transferred.

2.2 Postprocessing

Image processing is a powerful tool to read the information contained in an image and automate the process of data extraction. Images can be abstracted converting them to greyscale, smoothening them or coloring areas according to their size. The main idea of the postprocessing algorithm is to monitor predefined targets on building services. In the development process of the device, the first idea to track window opening has been to follow a geometrical approach using round objects attached to the window frame (see Figure 2). The intended post-processing steps were: the definition of a Region Of Interest (ROI), the conversion into greyscale or b/w, the smoothening through the deletion of objects smaller than 20 pixels. The key component is the object identification; for round objects, this is done through the calculation of the ratio of perimeter to surface area. However, round objects are often found throughout the image due to blur or light rays resulting in circular reflections. For these reasons, this option is discarded in favor of color recognition, detailed in the following.

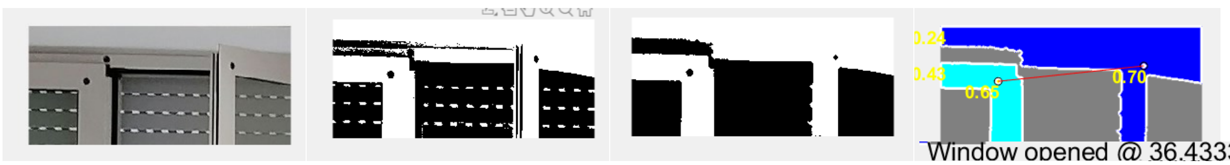


Figure 2: Abstracting an image into black/white, smoothening, and round object identification

2.3 The color recognition algorithm

Colors are more unique than the form of objects. In preliminary test series it has been shown that the color recognition is more reliable than the identification of round objects. It is to mention that the choice of a unique color - not being present in the surrounding environment included in the image - is essential.

The colored area recognition algorithm is coded in Matlab using tools of the image post-processing toolbox. To ensure privacy using a camera device, images are cut to a small region of interest, used for internal post-processing, and immediately deleted.

To find only the color-coded targets, an algorithm is run over the image filtering all pixels for certain RGB values. It must be considered that ambient conditions influence on the RGB values measured by the camera’s sensor and therefore all possible light conditions as shown in Figure 3 should be evaluated individually.

Figure 3: Camera perspective on classroom (left); Camera & Raspberry setup (right)

The pixels identified to be within the specified RGB range are saved into a matrix of the same dimensions as the image, referred to as *mask*. In a next step, noise (i.e., areas measuring less than 200 pixels) is removed from the mask.

To verify that the mask corresponds to the target on the window, a further check for geometry, size, and color ratio of the mask is made. The red targets on the windows are 3 cm wide and between 5 to 7 cm high. Therefore, the aspect ratio ranges between 0.4 to 0.6. Considering the camera sensor, lens and distance to wall, the size of the targets is around 40x18 pixels as shown in Table 1. As color codes, red is used for the windows, yellow for the shades and white for the lights given the overexposure if switched on. Each target is composed of shares of red, green, and blue which vary according to the chosen color, light conditions, camera sensor, and lens properties.

Table 2: RGB margins for different light conditions and targets

	Theoretical RGB value	Direct light	Diffuse Light	Artificial Light	Dark Light
Windows (red)	R: 255 G: 0 B: 0	R: 158-195 G: 56-97 B: 72-147	R: 113-202 G: 29-70 B: 35-73	R: 98-142 G: 17-37 B: 22-41	R: 31-97 G: 8-35 B: 11-40
Shadings (yellow)	R: 255 G: 255 B: 0	R: 204-255 G: 228-250 B: 104-184	R: 95-197 G: 96-194 B: 32-99	/	R: 31-95 G: 33-97 B: 9-79
Lights (white)	R: 255 G: 255 B: 255	/	/	Mean (RGB) > 210	Mean (RGB) < 210

Given that the ambient light conditions majorly impact on the colors seen, four different RGB ranges are tested as pre-sets: direct light, diffuse light, artificial light, and dark light. While programming the post-processing algorithm, they are individually assessed through 10 sample images for each condition and summarized in Table 2. In the current version, the algorithm tests each light condition separately and uses the most suitable one in terms of target size and ratio. Future developments foresee the implementation of the white balance of the camera sensor to retrieve the necessary information on the light situation.

If the mask passes the verification of RGB values, aspect ratio, surface area and color ratio, it is recognized successfully as "target" within the image. Otherwise, the post-processing algorithm asks for manual input. Subsequently, the coordinates of the target center are received and compared to the coordinates of the window or the shading if closed. To convert this pixel value into a percentage, angle, or metric value, the following Equations are used for the windows angle (1) and the shading position (2):

$$\alpha = acos(1 - d/d_{90}) \tag{1}$$

with: $d = x_{measured} - x_{closed}$; d_{90} = distance in pixels if window fully opened; $x_{measured}$ = current coordinates of target; x_{closed} = coordinates of target if closed

$$S_x = (x_{measured} - x_{closed}) * H \tag{2.1}$$
$$S_{\%} = S_x \,/\, H \tag{2.2}$$

with: $x_{measured}$ = current coordinates of target; x_{closed} = coordinates of target if shading is closed; H = height of window

0° 30° 60° 90°

Figure 4: Images used for calibration of windows, taken in different positions at specified angles

The received information is associated to the date and timestamp in the image's filename as described in section 2.1 and finally written into a csv-file for further post-processing and studies of occupant behavior. The *main* code calls subfunctions for windows, shading and lights. The postprocessing steps done to find the targets on windows are shown exemplified in Figure 5.

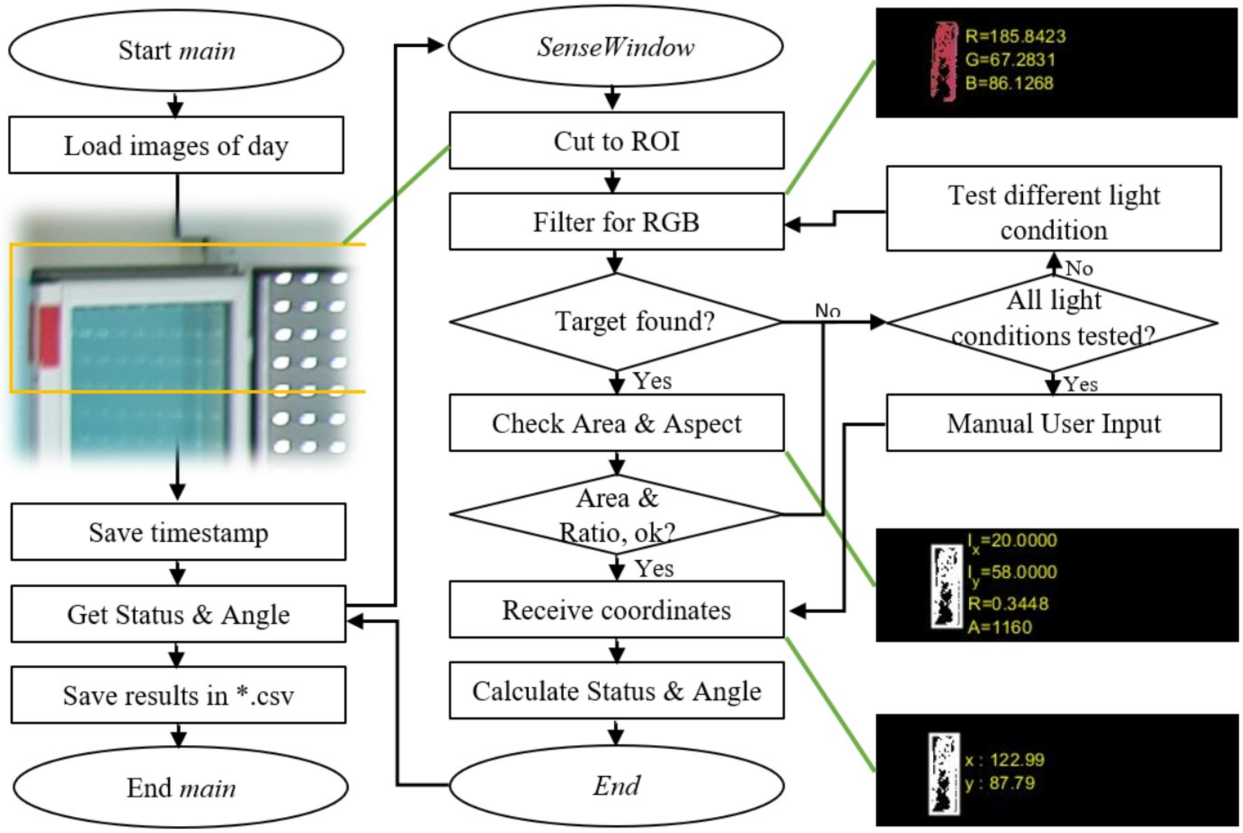


Figure 5: Flow chart showing the image post processing algorithm

It further needs to be mentioned, that for the given application the ROI's of shadings and windows might overlap. Therefore, classic edge detection algorithms would not work reliably. Colors are unique even if ROI's overlap. Additionally, monitoring lights is only possible using RGB, therefore this uniform postprocessing approach using RGB is chosen. However, we consider edge detection as a future development to increase reliability of the algorithm.

3. RESULTS

To test the device's accuracy and reliability, 35 representative sample images have been selected. Each image has been taken at different times of the day and of the year, in varying ambient and light conditions. The images were taken from the first three-month data set of the monitoring campaign. The verification dataset therefore provides 210 independent window states and angles, 105 shading state and position and 70 light state measurements. Every image has been validated manually to retrieve the exact status and position information of the monitored devices.

For windows and shades, it has been distinguished between status errors and angle or position inaccuracies. Status errors indicate that an open window has been detected as closed and vice versa. They are treated as the most relevant errors, whereas simple inaccuracies in opening angles are marked as major if greater than 20° or more than 5cm in the case of shadings. Else they are marked as minor errors.

To visualize status errors and the overall performance during verification, confusion matrices are shown in Figure 6. Each matrix shows the true positives in the upper left square, next to false negatives. In the lower squares the false positives are show on the left next to the true negatives on the right. The dataset has been balanced between opened (41.9 %) and closed windows (58.1 %) as well as turned-on (47.1 %) and turned-off lights (52.9 %). Just the shades are mostly in use (90.5 %) which is caused by the park position in which shades remained lowered at around 10 cm. If a shade lowered less than 20 cm would be considered as *in park position*, the set of shading sample images would be quite balanced, showing 42 % of shades in park position and 58 % of shades in use.

Actual Behavior (rows) / Device-reported Behavior (columns)

SensingWindows

	Open	Close
Open / In use	39.5 %	2.4 %
Close / Not in use	1.9 %	56.2 %

SensingShades

	In use	Not in use
Open / In use	90.5 %	0.0 %
Close / Not in use	1.9 %	7.6 %

SensingLights

	In use	Not in use
Open / In use	41.4 %	5.7 %
Close / Not in use	0.0 %	52.9 %

Figure 6: Confusion matrices showing status errors for windows, shades, and lights.

3.1 Windows

The status prediction of windows achieved an accuracy of 95.7 %. Evaluating further the false measurements, it should be noted that from a total of 9 status errors 8 occurred at opening angles lower than 20°. These accumulated inaccuracies at low aperture angles are due to the windows swiveling trajectory. Low angles result in a lower pixel resolution due to reduced target movement per angle of aperture, calculated in Equation 1. Therefore, slightly opened windows (< 20°) are considered as critical events.

If we add minor and major angle measurement errors to the evaluation, the accuracy of entirely correct measurement drops to 80 %. Minor errors in the angle measurement occur in 15 % of all measurements, whereas major errors in angle measurement only occur in 5 % of all cases. The summary of these results is shown as stacked column charts in Figure 7 where windows, shades and lights are numbered from left to right considering the field of view as shown in Figure 1. It is noted that the camera tends to slightly underestimate the opening angle. Further, there is evidence that major angle measurement errors are caused solely by window 2 and 5. Here the main cause of this increased errors on window 2 and 5 is that the camera position and the window's swiveling trajectory is rather unfavorable given that the target is swiveling towards the camera, moving only very little horizontally.

3.2 Shades

The status prediction of shades achieved an accuracy of 98.1 % from which 89 % have been entirely correct. 9 % of all measurements show minor position error of less than 5 cm, whereas only 2 % have been more than 5 cm beside the mark. It can be noted that no measurement errored showed more than 6 cm deviation. Furthermore, 42 % of all sample images showed shades lowered less than 20 cm, which leads to the assumption that the park position of a shade not in use is between 0 to 20 cm. Shading measurements showed the lowest fault rate with only 1.9 % of false measurements and an overall standard deviation of only 0.91 cm. It has been possible to achieve such high accuracy due to the simple geometric conception of a purely vertical moving target in contrast to a swiveling target such as the ones fixed on the windows. Figure 7 shows that the algorithm slightly tends to underestimate the shadow position which is rather not relevant given the low percentage and amount of deviation.

3.3 Lights

The status prediction of the lights achieved an accuracy of 94.3 % where the errors occurred entirely on light 1. Further investigations showed that 3 out 4 images with light error have a generally high illumination of the room with no shades in use and direct sun light resulting in a false negative measurement. Whereas 1 out 4 images showed a reflection on the frame of the light resulting in a false positive measurement.

3.4 Solutions to Common Errors

The preliminary validation of the device has been made on a three-month measurement campaign in a primary high school. Several potential improvements have been found.

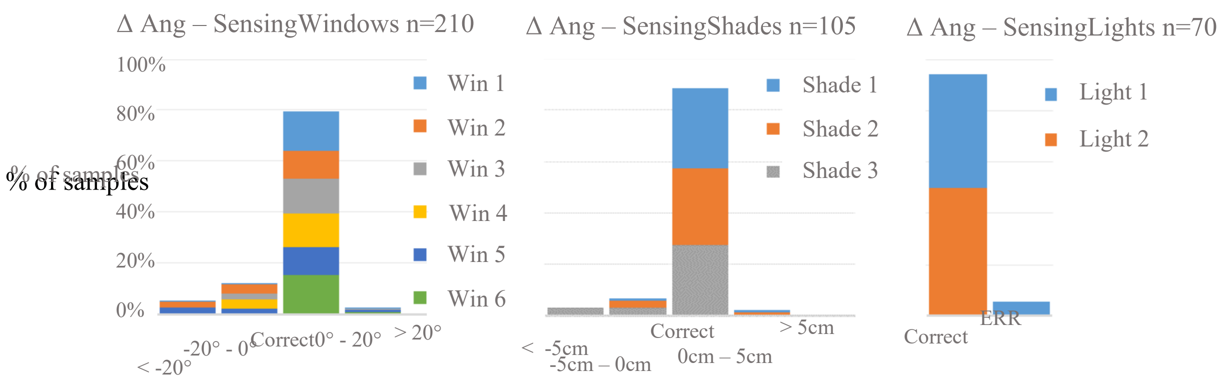


Figure 7: Stacked column charts showing measurement error categories

The accuracy of light measurements can be improved through the definition of multiple ROI's which would allow to avoid capturing the light frame avoiding reflections and double checking for illumination conformity throughout all captured ROI's. Else a manual operator interaction is requested (often at bright illuminance levels, shades completely open, etc.).

Shades could be bundled to be assumed to be *in park position* in case they are lowered less than 15 cm. However, given that the room illumination and window area in contact with the outdoor environment is affected even for small lowering distances, for detailed calculations of air flow they are significant.

In preliminary data processing attempts, it could be shown that measurement accuracy of windows can be increased through a simple check: if opening angles < 15° are persistent for multiple timesteps in a row, it is considered as truly opened at low angle. If an opening event of < 15° occurs only at a single timestep it is considered as measurement error and not being considered for postprocessing. Applying this additional rule, accuracy can be increased, given that most status errors occur at these low angles a window is considered as open only if the opening angle of < 15° remains for at least two timesteps in a row. However, these improvements will be future developments of the here presented measurement device. Finally, we will be working on accurate accuracy limitations due to resolution and geometric deformation of the image.

4. CONCLUSION

The present study reports the development of a camera-based device that is capable to monitor multiple windows, shadings, and lights operation simultaneously. The main feature is the possibility to measure opening angles and shading positions for a detailed analysis of the ventilation characteristics in a room. Furthermore, the device requires little wiring and effort to be set up. The core of the device is an image processing algorithm able to recognize color coded targets. It has been tested and evaluated in a High School in Morlupo, Italy. Considerations concerning the implementation of the device and of the algorithms are presented together with a preliminary validation based on a dataset of 35 independent images. Results show that the proposed monitoring system can monitor window opening angles and shading levels, dealing simultaneously with multiple windows, shadings, and lights. It therefore is a capable tool to monitor occupant behavior in different environments. The detailed validation showed an overall accuracy of 95.7 % for window openings, 98.1 % for shading operation and 94.3 % for the use of lights. Major attention has been paid to privacy-related issues, which are ensured through a strict image reduction to the necessary ROI and elimination of the image after having it post-processed automatically.

The analysis showed some limitations of the approach to be further addressed. The main limitations are the geometrical properties of the room, especially the window opening trajectory to the camera position within the room. A target swiveling towards the camera has a very low horizontal movement, resulting in higher inaccuracies during measurement. This is even amplified if windows are only slightly opened. Therefore, opening angles < 15° are considered as critical events and need to be handled with care. As a future development, the algorithm could be further stabilized through a double check if a critical angle < 15° occurs as a single event or for multiple timesteps in a row.

Future developments will focus on improving the reliability of the device through automized recognition of ambient conditions enabling the algorithm to automatically set the range of acceptable target ratio, color range and target area through a calibration sample dataset. Taking the post-processing algorithm one step further could involve machine learning techniques which would enable the algorithm to measure the use of building services even without mounted targets. Calibration could be done virtually using photorealistic renderings increasing automatization and requiring fewer manual interventions. A further application of the proposed device is thought to be from the outside of a building. Capturing an entire building façade would allow to monitor multiple windows simultaneously while ensuring higher levels of privacy.

The here presented monitoring device has been proven to be a capable and powerful tool to monitor behavioral patterns. Based on the obtained data accurate behavioral models can be developed to analyze and suggest improvements for the indoor air quality of classrooms. Moreover, the output data from this equipment can be used to obtain the window opening free area and perform calculation on the ventilation rate according to EN 16798-7.

REFERENCES

Alishahi, N., Ouf, M. M., & Nik-Bakht, M. (2022). Using WiFi connection counts and camera-based occupancy counts to estimate and predict building occupancy. *Energy and Buildings*, *257*, 111759. https://doi.org/10.1016/j.enbuild.2021.111759

Clark, B. K., Winkler, E. A., Brakenridge, C. L., Trost, S. G., & Healy, G. N. (2018). *Using Bluetooth proximity sensing to determine where office workers spend time at work*. https://doi.org/10.1371/journal.pone.0193971

Coley, D. A. (2008). Representing top-hung windows in thermal models. *International Journal of Ventilation*, *7*(2), 151–158. https://doi.org/10.1080/14733315.2008.11683807

EN. (2018). *UNI EN 16798-7 Energy Performance of buildings - Ventilation for buildings - Part 7: Calculation methods for the determination of air flow rates in buildings including infiltration*.

Fritsch, R., Kohler, A., Nygård-Ferguson, M., & Scartezzini, J. L. (1990). A stochastic model of user behaviour regarding ventilation. *Building and Environment*, *25*(2), 173–181. https://doi.org/10.1016/0360-1323(90)90030-U

Haldi, F., & Robinson, D. (2009). Interactions with window openings by office occupants. *Building and Environment*, *44*(12), 2378–2395. https://doi.org/10.1016/j.buildenv.2009.03.025

Kim, M., & Tzempelikos, A. (2022). Performance evaluation of non-intrusive luminance mapping towards human-centered daylighting control. *Building and Environment*, *213*(January), 108857. https://doi.org/10.1016/j.buildenv.2022.108857

Medellin, A. (2020). *The New Raspberry Pi Camera Is a Worthwhile Upgrade*. The New Raspberry Pi Camera Is a Worthwhile Upgrade. https://www.premiumbeat.com/blog/new-raspberry-camera-upgrade/

O'Brien, W., Wagner, A., Schweiker, M., Mahdavi, A., Day, J., Kjærgaard, M. B., Carlucci, S., Dong, B., Tahmasebi, F., Yan, D., Hong, T., Gunay, H. B., Nagy, Z., Miller, C., & Berger, C. (2020). Introducing IEA EBC annex 79: Key challenges and opportunities in the field of occupant-centric building design and operation. *Building and Environment*, *178*(February). https://doi.org/10.1016/j.buildenv.2020.106738

Park, J., & Choi, C. S. (2019). Modeling occupant behavior of the manual control of windows in residential buildings. *Indoor Air*, *29*(2), 242–251. https://doi.org/10.1111/ina.12522

Speak, A., Montagnani, L., Wellstein, C., & Zerbe, S. (2021). Forehead temperatures as an indicator of outdoor thermal comfort and the influence of tree shade. *Urban Climate*, *39*(August), 100965. https://doi.org/10.1016/j.uclim.2021.100965

Stazi, F., Naspi, F., Ulpiani, G., & Di Perna, C. (2017). Indoor air quality and thermal comfort optimization in classrooms developing an automatic system for windows opening and closing. *Energy and Buildings*, *139*, 732–746. https://doi.org/10.1016/J.ENBUILD.2017.01.017