Mobile Application to Support Facade Renovation

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Abstract: We present a mobile application that enables end users to quickly calculate the size of a building facade. Our goal is to support the renovation of facades, as their costs are mainly determined by the surface area. We developed an image-based approach that consists of four steps. First, we measure the facade width using augmented reality (AR) functionalities of modern smartphones. In our evaluation, this measurement achieves an average accuracy of 98.5 %. In the second step, the user takes a photo of the facade and marks its contours. All information is transferred to a server that rectifies the photo. The result of step three is a distortion-free orthophoto of the facade, with the correct ratio of width to height. The fourth and final step is AI-based image recognition to identify facade elements such as windows, doors, and roofs. The facade area is calculated by subtracting the area of facade elements from the total area. We evaluated our application on ten different buildings and achieved an average accuracy of 97.5 % for the facade area.

Keywords: Facade renovation, Mobile applications, Augmented reality (AR)

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1 Introduction

Climate change continues to progress and requires consistent action to reduce greenhouse gas emissions. The building sector plays a key role, as it is a major contributor to emissions due to its high energy demand for heating and electricity. Older buildings in particular lose significant amounts of energy due to poor insulation. Energy-efficient renovation of the facades is therefore urgently needed, but the implementation of renovation measures still depends heavily on the motivation of homeowners. They often do not know how much a renovation will cost and are overwhelmed by the complexity of the process. There are online calculators providing cost estimates, but they need the area of the facade as input, which is often unknown to homeowners. A simple and easy-to-use tool for calculating the facade area has the potential to significantly reduce the entry barrier to the renovation process.

In this paper, we present such a tool for modern smartphones. We developed an image-based approach since it is easy to use and does not require any special hardware. We use AI-based image recognition to calculate the facade area in pixels. To be able to convert this information to square meters, we need a reference size from the real world. Our app uses Augmented Reality (AR) functionalities of modern smartphones to measure the facade width as a reference size.

2 Related Work

There are a few existing methods to calculate the area of a building facade. First, it is of course always possible to use a measuring tape. This approach is simple but requires time. It can even become a dangerous endeavor if a building is very high. Laser measuring devices provide a safe and accurate alternative, but they are expensive and not applicable to complex surfaces.

Professional solutions are based on 3D point clouds, which are recorded using LiDAR devices (Light Detection and Ranging). Point clouds have been used to reconstruct building facades [1]. The results are very accurate, but problems can arise if the laser hits transparent surfaces, which can lead to gaps and other measuring errors [2]. Also, scanning a building facade with such a professional device is time-consuming and expensive. There is also a lack of automated data processing [1]. Modern AI-based processing approaches are promising, but still require manual effort [3].

Another alternative is provided by close-range photogrammetry [4]. Here, multiple images are taken around an object with convergent camera orientations. Through mathematical techniques such as image registration and bundle adjustment, a 3D model can be derived, which in turn allows the facade to be measured. However, this approach requires planning effort, careful acquisition, sometimes even sophisticated gear and setups [5], as well as complex post-processing. Similar to laser scanning, it is therefore not suitable for private homeowners who simply want to know the area of their facade.

For this reason, we present a low-cost app-based solution in this paper. Our app uses augmented reality (AR), which has already been recognized as a valuable technology in the building construction sector [6]. The ARKit and ARCore frameworks for the iPhone and Android phones, respectively, provide means for developers to integrate AR functionality in their mobile apps [7]. Maneli and Isafiade have evaluated these frameworks with respect to the measuring quality [8], [9]. They report accuracies of 89.42 % (ARCore) and 97.52 % (ARKit), increasing to 99.63 % (ARCore) and 99.26 % (ARKit) depending on the distance, which is more than suitable for the purpose of this work.

3 Approach

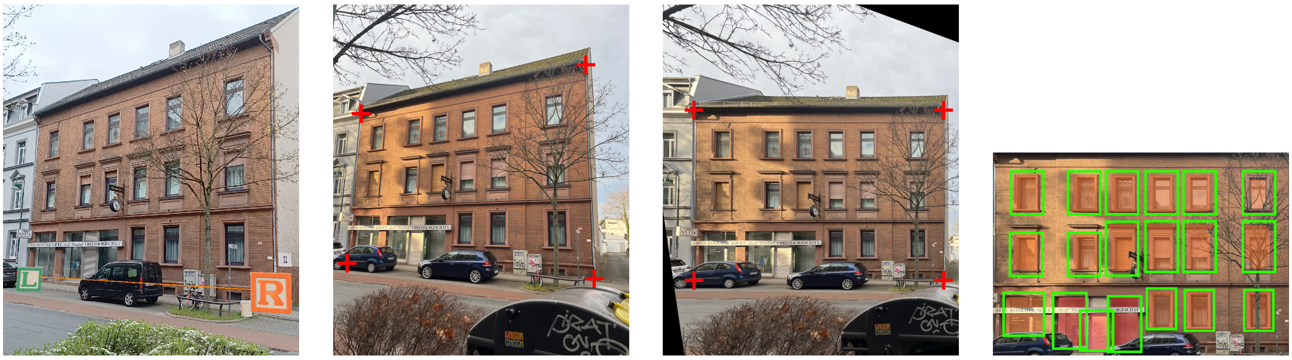
With our approach we want to create both an easy-to-use application with low hardware requirements and sufficient accuracy for cost estimation. To calculate the facade area we use four steps:

1. Measuring the facade width
2. Take a photo of the facade and define its contour
3. Rectifying the photo of the facade
4. Identify facade elements

Steps 1 and 2 are realised within a smartphone app, while steps 3 and 4 are carried out on a server. The results of each step are shown in Fig. 1.

3.1 Measuring the facade width

The first step is to measure the width of the facade. This enables us to convert a size in pixels into metric data later, thus we call it *reference size*. Instead of the facade width, any other object such as



(a) AR width (b) Distorted image (c) Rectified image (d) Object detection

Figure 1: Results of each step of the process. The first figure shows the AR measurement of the facade width. The second figure shows the distorted photo taken by the user with the corner points of the contour. In the third figure the photo was rectified and in the last figure, facade elements have been identified.

windows or doors could have been used as a reference, too. However, the width of the facade is an easily recognisable size and thus well suited.

For distance measurement, we rely on the augmented reality (AR) capabilities of modern smartphones. To implement the mobile application, we use the AR framework ViroReact [10], which provides the AR capabilities of the smartphone in a React Native application. The user sees a live camera feed and can put virtual objects in the world. We use this to mark the bottom left and right corners of the facade as shown in Fig. 1a. Since ViroReact provides 3D position of the objects in a metric space, we can calculate the distance between them and thus the width of the facade.

3.2 Taking a photo of the facade and defining its contour

Once the facade width has been determined, the user takes a photo of the whole facade. It is important to ensure that the entire facade is visible since missing parts will not be included in the final area calculation.

Next, the user defines the contour of the facade in the photo, as shown in Fig. 1b. Since facades can have multiple corner points, the app provides three possible shapes as illustrated in Fig. 2. The user drags the corner points of a selected shape onto the photo taken before.

Shape one in Fig. 2 defines a facade with four corner points and is a simple rectangle. It is extended in shape two by an attic storey, which leads to five corner points. These two shapes are called *simple contours* since they identify the whole facade area. Although the majority of existing facades can be described by them, we recognise that there are also more complicated facades. For these cases, we

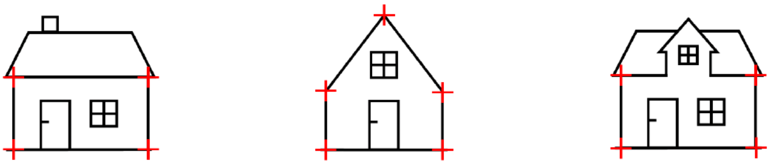


Figure 2: Different shapes for defining the facade contour.

defined a third shape, in which only a rectangular base area is selected. The upper part of the facade will be defined by an AI-based image recognition in step 4 of our process.

Instead of letting the user define the contour of the facade, we could have used a purely AI-based image recognition solution. However, our tests showed that this is prone to errors. Especially the separation of neighbouring houses or the handling of facades partially obscured by vegetation, parked cars, and other objects is too often inaccurate and did not satisfy our targeted quality.

3.3 Rectifying the photo of the facade

For the following steps, the photo, reference size, and corner points of the contour are sent from the smartphone app to a server. This reduces load on the smartphone app and improves performance.

To calculate the final facade area, we need an image in which each pixel covers the same metric area. However, the photo was taken with distortions caused by camera angle and perspective. To get a distortion free image, we use the rectification method by Zhang and He [11]. It takes four points in the distorted photo that form a rectangle in real world. In our case, we use the four lower corner points of the contour defined by the user. With these points, Zhang and He calculate the aspect ratio from width to height and return a formula for correction. We apply this to the whole photo and get a distortion-free image of the facade as shown in Fig. 1.

It has to be noted that this only applies to planar objects. Wall protrusions like bay windows are not correctly rectified and will lead to errors in the later area calculation.

3.4 Identifying facade elements

Once the image has been rectified, AI-based image recognition is used to classify the pixels. If a simple contour was defined in step 2 of our process, only the area within the contour is analysed. This ensures that no elements of neighbouring facades are taken into account. If a complex contour was selected, we additionally check the area above the upper edge. In this way, we can add additional pixels to the facade area, even if they were not included in the contour.

We use the AI framework GroundingDINO [12] to detect four classes: facade, window, door and roof. Multiple classifications of the same object are avoided by using non-maximum suppression (NMS). Within the recognized bounding boxes, we perform a segmentation to get the pixel-wise boundaries of the detected objects. For this, we use the SegmentAnything model [13]. Examples of the classification and segmentation results are shown in Fig. 1d.

We define the *total area* as the area covered by the contour, plus any facade area found above the upper edge of the complex contour. From this total area, we subtract all detected facade elements (windows, doors, roofs) to get the actual facade area. Note that this facade area is not the same as the area segmented as a facade. If cars, vegetation or other objects cover parts of the facade, they are not included in the segmentation. However, as long as they are within the contour, we still count their pixels for the facade area. This is a trade off. If, for example, a window is covered by a car, we interpret the area incorrectly as facade, but in our experience, it is much more likely that normal facade area is covered. For the same reason, we use the rectangular base area of complex contours for the total area and only rely on AI for the upper parts where occlusion is less likely.

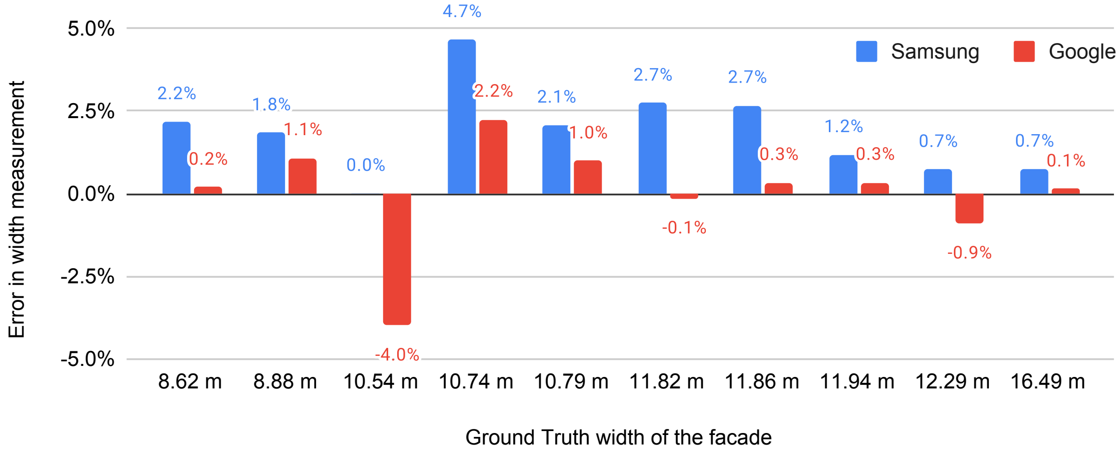


Figure 3: Error in the AR-based measurement of the facade width of the ten buildings from our study.

Finally, the facade area in pixels is converted to square meters using the reference size from step 1. The area and segmented image are sent to the app for display, allowing users to verify the process.

4 Evaluation

We evaluated the accuracy of the individual steps as well as the overall process to get clearer insights into the strengths and limitations of our approach. The app design requires on-site evaluation, so we used ten real buildings in the city of Darmstadt, Germany. They are representative for our target audience owning detached houses. For them, we had a Level of Detail (LoD) 2 model as ground truth, which was reconstructed from a point cloud.

We measured the facade width using our app on a Samsung Galaxy A32 and a Google Pixel 5 to assess hardware influence. Fig. 3 compares our results with the LoD 2 model. Both smartphones tend to overestimate width, with the Google phone being more accurate. It has an average error of 1 % (median 0.6 %, variance 1.5), while the Samsung device has 1.9 % (median 2 %, variance 1.8). This is an improvement on previous studies [8], [9], which had around 10 % error, and supports findings that devices with more powerful hardware achieve greater accuracy. However, no clear trend emerged regarding smaller or larger distances being measured more accurately.

To evaluate the rectification, we compared the height of ten buildings from the LoD 2 model with the calculated height. Since we wanted to evaluate the isolated accuracy of the rectification, we used the width of the LoD 2 model as ground truth to calculate the height. Our test buildings were between 9 and 16 m high and were reconstructed with an average error of 0.5 % (median 0.45 %, variance 0.13). In contrast to the width, the height tends to be underestimated. The intensity of the distortion had no influence on rectification. However, the more distorted the image, the more difficult it was to set the corner points in the right place. Incorrectly positioned corner points reduced the rectification quality.

To evaluate the size of the facade and its elements, we used texture information from the LoD 2 model, manually marking pixels and converting them into square meters. Due to the low visual quality of textures, object boundaries were sometimes unclear. We took this uncertainty into account by defining minimum and maximum values for each area. Overall, we got an average error of 4.1 % with the

Samsung device (median 3.1 %, variance 11.9) and 1.12 % with the Google smartphone (median 0 %, variance 6.1) The variance was noticeably higher than in other steps due to the AI-based image recognition, which relies on probabilities and is less consistent. Various error sources are discussed in Section 5. No clear trends emerged across different house categories, as both good and poor results were observed in all three.

Excess material is common in construction due to standardized packaging of materials like paint, plaster, and insulation. Our overall deviation of 2.5 % is within an acceptable range. There are no legal requirements or universal standards for material quantity calculations or cost estimate accuracy [14]. Literature suggests deviations of 30–40 % are typical for initial estimates [15], the accuracy of our application can therefore be considered accurate.

5 Discussion

In Section 4, we demonstrated that our approach enables accurate facade area calculation, though some challenges remain. The overall accuracy of the application highly depends on the accuracy of the reference size, as it determines the pixel-to-meter scale. Section 4 shows that it can be determined with a small error in general. However, occlusions from vegetation, parked cars, or poor lighting can affect its precision. Future advancements, such as LiDAR sensors in smartphones, may improve AR-based measurements.

Another challenge is the accuracy of corner points, which impacts image rectification and total area calculation. While manual corner point setting helps reduce errors from occlusions, obstacles in front of house corners can still prevent precise placement.

As noted in Section 4, image recognition can be imprecise, particularly for complex contours where additional processing is needed to determine the facade area. Fig. 4 highlights the error sources of an incorrect area calculation, marked in red. In error source 1), part of another house was mistakenly identified as facade area—an issue that occurs only with complex contours since simple

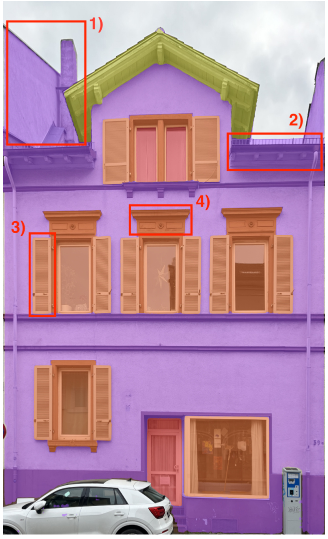


Figure 4: Example of an incorrect facade area calculation. Four different types of errors are highlighted in red.

ones completely rely on user-defined boundaries. Image recognition also struggles with certain facade elements, as shown in 2), 3), and 4). Some roof elements in 2) are not recognized as such and windows are not always detected correctly. In 3), window shutters were classified as additional window areas and as a result, too much was subtracted from the calculated facade area. Another problem is shown in 4) where window cornices are recognised as part of the windows instead of the facade. This results in the same problem as with the shutters and leads to an incorrect facade area calculation.

These problems could be avoided by using a more specific model that is trained on facade elements. However, to this date, there is no such model or dataset that is suitable for our use case [16]. Additional user input could also help improve the accuracy of the image recognition by allowing the user to correct the detected objects or add missing ones.

6 Conclusion

We presented a smartphone app that enables users to measure facade areas using augmented reality and AI-based image recognition. The application is easily accessible, does not require any additional equipment or external parameters, and is entirely based on the use of a modern smartphone.

The facade area can be calculated with an average accuracy of 97.5 %, which is within the usual margins for cost estimation. The accuracy depends on both the performance of the smartphone being used and the precision of the user interactions. The latter can be investigated in a future user study. The app is suitable for a wide range of buildings, including those with complex facades. However, the accuracy of the image recognition is crucial for the overall accuracy of the facade area calculation and can lead to significant deviations. Future work can concentrate on minimizing these errors in image recognition by using a more powerful model.

Although other methods for measuring facade areas exist, they often require expensive equipment or special knowledge. Therefore, our approach is a valuable addition to the existing methods since it can be used by anyone with a smartphone. We believe that our application has the potential to significantly reduce the entry barrier for homeowners to consider energy-efficient renovation options.

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