

Low-Cost Webcam Camera and GNSS Integration for Updating Home Data Using AI Principles

Hepi Hapsari Handayani, Mokhammad Nur Cahyadi*, Agus Budi Raharjo, Failaql Haq

*Corresponding Author

Sepuluh Nopember Institute of Technology, ITS Sukolilo Campus, Surabaya 60111, Indonesia*

hapsari@geodesy.its.ac.id, cahyadi@geodesy.its.ac.id, agus.budi@its.ac.id, 6016212006@mhs.its.ac.id
Tel *: +62 857-7614-2444

Abstract

PDAM Surya Sembada Surabaya City responds to Surabaya's water service demand by pioneering a cost-effective mobile mapping tech. This innovation integrates 3 MP webcams, GNSS, and IMU sensors to update customer building data efficiently. Precise photo data with location and movement info within 1-meter proximity captures accurate building coordinates. Applying georeferencing and Cosine Similarity reduces redundant data by 50%. GNSS, IMU sensors, and VGG-16 model aid data collection and analysis. This comprehensive approach optimizes PDAM Surabaya's operations, ensuring timely and accurate customer updates amid Surabaya's population growth, promising enhanced service delivery while managing costs.

Keywords: Mobile Mapping, GNSS, IMU, Similarity;

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1.0 Introduction

PDAM (Regional Water Supply Company) Surya Sembada Surabaya City is a regional government-owned enterprise providing drinking water in Surabaya and its surrounding areas. The company was recognized as a regional company in 1976 (Regional Regulation of Surabaya II Level Region Number 7 of 1976 Concerning Regional Water Supply Company, 1976). Surabaya, the second largest metropolitan city after Jakarta, experienced high growth due to the natural rate of urban population growth and the process of urbanization. Based on the Surabaya Central Statistics Agency (2021), in the period 2010 to 2020, the population growth rate in Surabaya City reached 3.94%. In 2020, PDAM Surya Sembada Surabaya City provided clean water to 580,000 customers in the housing, government, private, industrial, public social, and port sectors, with 80% being household customers (Kurniawan, 2020).

The population growth rate in Surabaya City (2010 to 2020) reached 3.94%, encouraging increased demand for clean water services from the Regional Water Supply Company (PDAM). This drives the need to adjust charges for customers whose water usage has changed significantly for the business or social class of users. The charge determination carried out by PDAM considers the building or customer's house. Charge determination significantly affects PDAM's income and customer cost burden because PDAM applies a subsidy policy for small household classification customers. Regular updates are needed to ensure that price and subsidy determination are targeted. PDAM needs a comprehensive survey of all customers in Surabaya to update customer building data. Surveys are usually carried out by deploying personnel to conduct surveys one by one to each PDAM customer. This method requires much labor and not a small cost. Therefore, to save time and cost, we offer mobile mapping technology where the tool is installed in a car to record the surrounding buildings while the car is moving.

Generally, mobile mapping technology uses a LiDAR sensor equipped with GNSS, but this technology requires a high cost. Therefore, this study objective to develop a low-cost mobile mapping technology. Our device using 4 webcam sensor added with GNSS and IMU sensors. The camera used has a specification of 3 MP with a resolution of 720 and a 78° diagonal field of view. The principle of this invention is to integrate four webcam camera sensors and GNSS with IMU to acquire photo data equipped with location data (latitude, longitude) and IMU (roll, pitch, yaw). The acquisition is carried out at every movement of 1 meter or less around the PDAM

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customer's building. The data obtained will be processed and analyzed using a Georeferencing method to obtain the coordinates (latitude, longitude) of the customer's building. The results of this study are expected to provide a solution for PDAM Surabaya in updating customer building data efficiently and at a low cost.

2.0 Literature Review

2.1 Mobile Mapping

Mobile mapping is a technology that uses portable mobile devices such as smartphones or tablets to collect and store geospatial data. In the field of asset management, mobile mapping can be used to improve the efficiency and accuracy of data collection, as well as to facilitate decision-making processes.

One study found that mobile mapping technology can be used to improve the maintenance and management of utility infrastructure, such as water and gas pipelines (Lopez et al., 2017). The study found that mobile mapping can help reduce the time and cost of inspections and improve the accuracy and reliability of data collection.

Another study explored the use of mobile mapping for asset management in transportation, specifically the maintenance and repair of highway assets and pavement (Farhadmanesh et al., 2021). The study found that mobile mapping technology using photogrammetry can be cheaper than LiDAR and photogrammetry as a reliable alternative technology only in favorable illumination conditions. Overall, the literature suggests that mobile mapping technology has the potential to revolutionize the way assets are managed and maintained by providing accurate, real-time data and enabling more informed decision-making.

2.2 Cosine Similarity

Cosine similarity is a measure of similarity between two non-zero vectors, calculated as the cosine of the angle between the vectors. It is often used in natural language processing and information retrieval to determine the similarity between two documents or pieces of text. However, cosine similarity can also be applied to other data types, including images.

One study found that cosine similarity can be used to improve the accuracy of image classification by taking into account the visual content of the images rather than just the presence or absence of specific features (Cao et al., 2014). Another study demonstrated the effectiveness of cosine similarity in image retrieval, showing that it can be used to improve the precision and recall of search results (Wang et al., 2014).

Cosine similarity has also been applied in image recommendation systems, with research showing that it can be used to generate more accurate and relevant recommendations for users (Zhou et al., 2018). Other studies have explored the use of cosine similarity for image clustering and similarity analysis, with promising results (Huang et al., 2016; Xu et al., 2017). Overall, the literature suggests that cosine similarity is a valuable and effective measure of similarity for a variety of image-based applications, including classification, retrieval, and recommendation systems.

2.3 Transfer Learning

Transfer learning is a machine learning technique that uses knowledge and skills learned from one task to improve the performance of a different but related task. It is often used in deep learning, where it can be used to improve the efficiency and effectiveness of neural network models.

One study found that transfer learning can improve the performance of natural languages processing tasks, such as language translation and text classification, by using pre-trained language models as a starting point (Pan & Yang, 2010). Another study demonstrated the effectiveness of transfer learning in computer vision, showing that it can be used to improve the accuracy of image classification and object detection tasks (Girshick, 2014).

Transfer learning has also been applied in medical image analysis, with research showing that it can improve the accuracy and generalizability of deep learning models for tasks such as cancer diagnosis and treatment planning (Shin et al., 2016). Other studies have explored the use of transfer learning for various applications, including speech recognition and natural language generation (Lu et al., 2017; Radford et al., 2018). the VGG16 model extract features from photos.

Furthermore, cosine similarity may be used to calculate feature similarity. Cosine similarity is a method for determining the similarity of two documents or feature. The cosine similarity method is utilized to seek similarities such as color characteristics, texture patterns, and product forms to eventually be used to make product recommendations to image-based users (Laksito et al., 2022). Overall, the literature suggests that transfer learning is a powerful and effective technique for improving the performance of machine learning models, particularly in the context of deep learning.

2.4 VGG 16

VGG 16 is a convolutional neural network (CNN) model developed by the Visual Geometry Group at the University of Oxford. It is a deep learning model trained on a large dataset of images and can be used for various image classification and object detection tasks.

One study found that VGG 16 can achieve state-of-the-art performance on the ImageNet dataset, a large dataset of images used for image classification and object detection tasks (Simonyan & Zisserman, 2014). Another study demonstrated the effectiveness of VGG 16 in the context of object detection, showing that it can be used to improve the accuracy of object detection in real-world images (Ren et al., 2015).

VGG 16 has also been applied in medical image analysis, with research showing that it can be used to improve the accuracy and generalizability of deep learning models for tasks such as cancer diagnosis and treatment planning (Shin et al., 2016). Other studies have explored using VGG 16 for various applications, including image segmentation and generation (Noh et al., 2015; Goodfellow et al., 2014).

The literature suggests that VGG 16 is a powerful and effective deep-learning model for various image-based tasks, including classification, object detection, and medical image analysis.

2.5 Georeferencing

Georeferencing is the process of assigning spatial coordinates to a map or other geospatial data to enable its integration with other geographic data sets and spatial analysis and visualization. It is an essential step in creating and using digital maps and other geospatial data.

One study found that georeferencing can be used to improve the accuracy and effectiveness of spatial analysis and visualization by enabling the integration and overlay of multiple data sets and the creation of more accurate and realistic maps (Goodchild et al., 2007). Another study demonstrated the potential of georeferencing for environmental monitoring and management by using georeferenced data to analyze and visualize patterns and trends in land use and land cover (Lin et al., 2012).

Georeferencing has also been applied in urban planning and development, with research showing that it can be used to create more accurate and effective plans and policies (Lopez et al., 2013). Other studies have explored the use of georeferencing for various applications, including transportation planning and disaster management (Kim et al., 2014; Chen et al., 2015).

Overall, the literature suggests that georeferencing is a critical and valuable tool for a wide range of applications, enabling the integration and analysis of geospatial data and the creation of more accurate and informative maps.

3.0 Methodology

This research integrates a multisensor that combines camera and GNSS technology and uses AI instruments to automate. For a complete methodology, see the following steps.

3.13.1 Flow Chart

PDAM customer building surveying in Surabaya with Low-cost Mobile mapping mounted on a car. Data is acquired every 0.5 meters by storing photo data from each installed camera and adding coordinate information (latitude and longitude) and IMU from the installed GNSS sensor. The selected areas are several areas with the types of houses that represent the categories of houses that the PDAM has determined. Each building will have several images were taken, which causes redundancies, so it needs to be reduced to leave one building data for each customer so that acquisition data can be georeferenced with existing customer data.

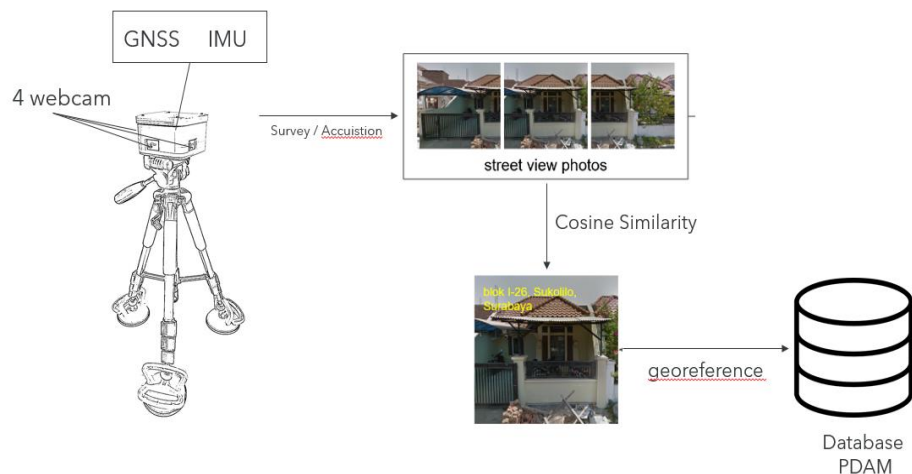


Fig. 1: Flow chart

3.2 Cosine Similarity Analysis using VGG 16 Model

Transfer learning is a technique used in machine learning to apply a pre-trained model to different datasets. A pre-trained model can be provided as an "initial model" which is then negotiated and retrained on a new dataset. This is useful because a pre-trained model has learned valuable features from a large dataset, thereby improving the model's performance on smaller or similar datasets.

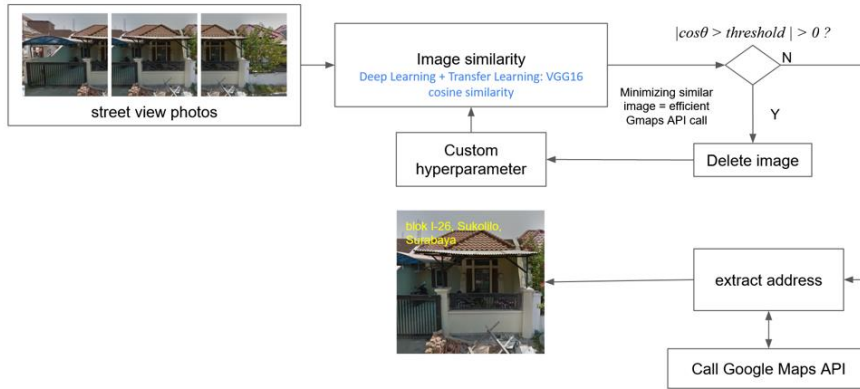


Fig. 2: Cosine similarity analysis flow chart using transfer learning VGG-16 model

VGG16 is one of the pre-trained convolution models on ImageNet, which is a massive dataset with over a million images categorized into 1000 classes. This model has been trained to extract useful features from images and can be used as an initial model for transfer learning.

Cosine similarity analysis is a technique used to calculate two vectors' similarity. Vectors can represent various representations, including features produced by convolution models such as VGG16. We can determine how similar the two vectors are by calculating the cosine similarity between the two feature vectors.

Reducing lookalike images is the process of identifying and eliminating images very similar to one another from a dataset. This is useful because it reduces bias in the model trained with the dataset. To do this, we can use VGG16 to extract features from each image and then calculate the cosine similarity between each pair of images. If the cosine similarity between the two images is too high, then one of the images can be considered similar and removed from the dataset.

The building image dataset will be used to train the building recognition model. We can use the VGG16 model to extract features from each image and then calculate the cosine similarity between each pair of images. If the cosine similarity between the images exceeds the threshold value, then one of the images will be considered similar and removed from the dataset. Thus, only one image will be left for each building taken.

4.0 Findings & Discussion

AI Development for a low-cost GPS-integrated data acquisition application system. The database has been designed and then built with PostgreSQL software. The image below is the SQL code for creating entity tables according to the database design as an implementation of the database design that has been made. Also built an Artificial Intelligence (AI) system for the classification of building land that has been acquired by mobile mapping based on the Azure Kinect camera.

```

1.4. Load Model: VGG-16 Transfer Learning
# Use VGG16 model as an image feature extractor
image_input = Input(shape=(224, 224, 3))
model = VGG16(input_tensor=image_input, include_top=True, weights='imagenet')
layer_name = 'fc2'
feature_model = Model(inputs=model.input, outputs=model.get_layer(layer_name).output)

Downloading data from https://github.com/fchollet/deep-learning-models/releases/download/v0.1/vgg16_weights_tf_dim_ordering_tf_kernels_h5_553467896/553467896 [*****] - 365 0us/step

2. Image Comparison and Elimination using Cosine Similarity

clone git

[ ] #@title clone git
!rm -rf streetviewSample

!git clone https://github.com/agusbudi/streetviewSample # clone repo

Cloning into 'streetviewSample'...
remote: Enumerating objects: 699, done.
remote: Counting objects: 100% (6/6), done.
remote: Compressing objects: 100% (5/5), done.
remote: Total 699 (delta 0), reused 5 (delta 0), pack-reused 693
Receiving objects: 100% (699/699), 85.41 MiB | 23.83 MiB/s, done.
  
```

```
CREATE TABLE meteran (
    id_meteran INT PRIMARY KEY,
    id_zona INT NOT NULL,
    FOREIGN KEY (id_zona) REFERENCES zona (id_zona),
    kode_wilayah VARCHAR (30) NOT NULL,
    FOREIGN KEY (kode_wilayah) REFERENCES wilayah (kode_wilayah),
    id_tarif INT NOT NULL,
    FOREIGN KEY (id_tarif) REFERENCES Golongan_tarif (id_tarif),
    nomor_meteran VARCHAR (30) NOT NULL,
    nomor_pelanggan VARCHAR (30) NOT NULL,
    nama_pelanggan VARCHAR (30) NOT NULL,
    tahun_instalasi DATE NOT NULL,
    alamat TEXT NOT NULL,
    NJOP VARCHAR (30));
```



Fig 3. (a) Development of an Artificial Intelligence (AI) system for building classification (b) Creation of PDAM customer meter asset database (c) Display of photo data for building classification using AI

The distribution of customer location points in subzone 102 before and after being updated using the integration of an Android-based survey application and low-cost GNSS. In the previous customer location recording method, the location was obtained using a GNSS mobile phone so that the location could have been better and far from the actual location. In the map below, the customer points recorded using mobile GNSS appear to be fewer due to the large number of customer points that have strayed far, even being detected outside subzone 102.

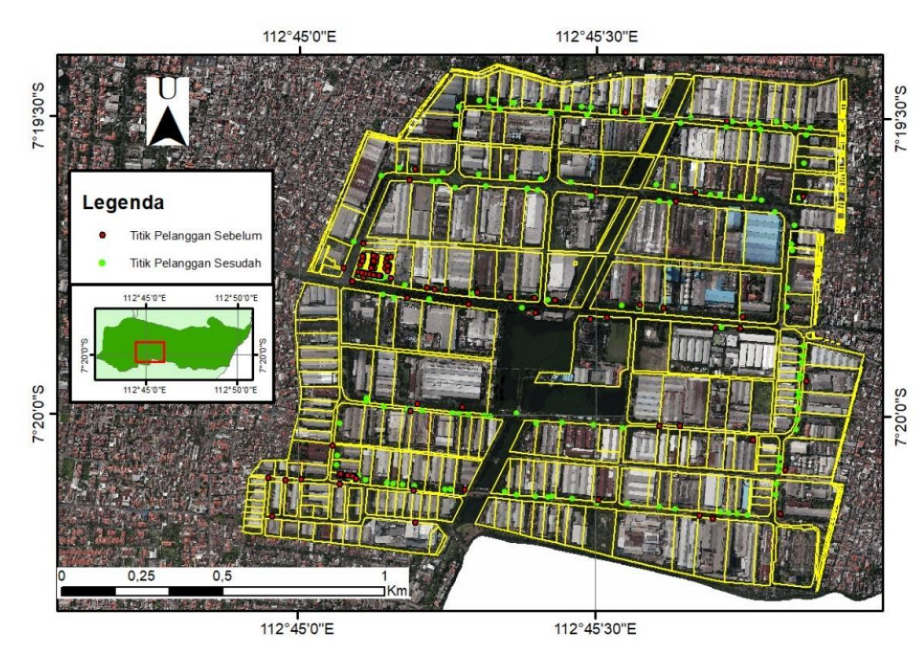


Fig 4. Subzone 102 subscriber points as measured by low-cost GPS innovation products

In testing system functionality, recording the condition of the water meter asset was also carried out in the 531 service subzone, with the distribution of customer locations visualized in Figure 4 and Figure 5. On the map below, customer points recorded using an Android-based survey application and low-cost GNSS integration show that the results differ from previous data recorded using the phone's internal GNSS. This is due to the large number of customer points that have strayed far and piled up at one customer location.

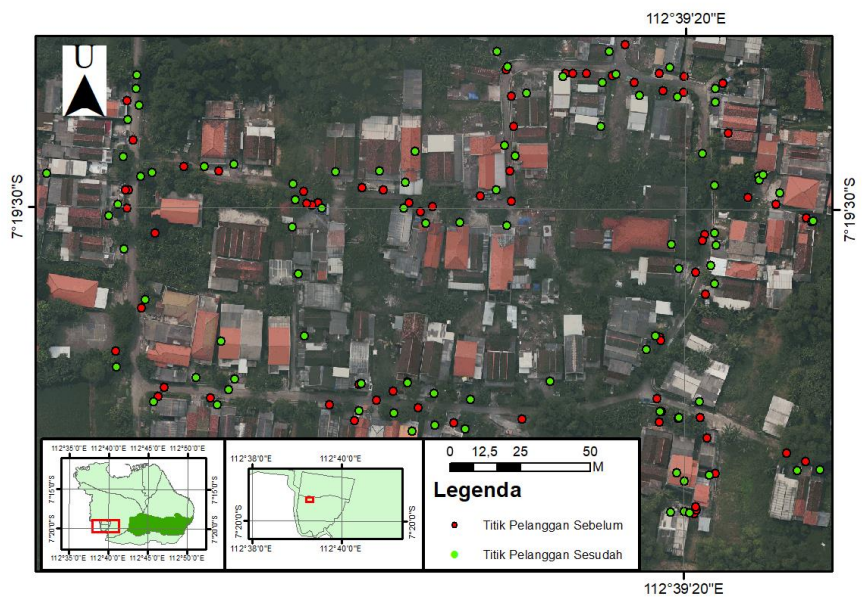


Fig 5. Subzone 531 customer points using low-cost GPS innovation products

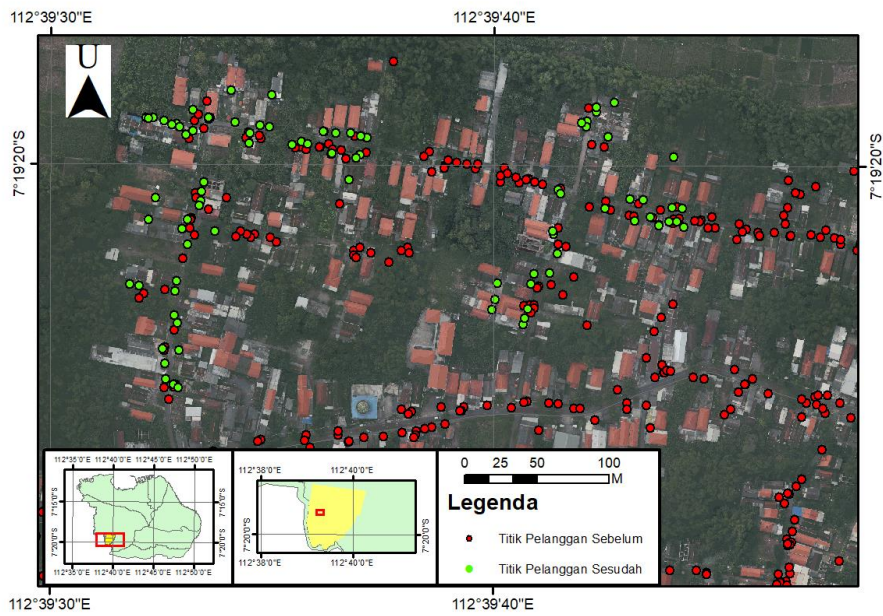


Fig 6. Subzone 531 customer points using low-cost GPS innovation products

5.0 Conclusion & Recommendations

By using a low-cost mobile mapping tool, the need for customer building surveys can be carried out more efficiently than using the usual method of deploying surveyors to take photos of each building. However, this method needs to improve in the presence of image redundancies. To eliminate image redundancies, cosine analysis is performed so that one image remains for each customer. GNSS and IMU data also helps to carry out the process of georeferencing existing data so that it can be updated with new data. To improve this study, We need to consider the building location. Some areas have identical buildings. It could be removed because of the similarities but actually it is different, or by using real-time building identification to only save full building pictures.

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