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Review

PhD Thesis Title: Deep Learning Methods for Automated Urban Monitoring System using Synthetic Aperture Radar

Tytuł pracy w języku polskim: Metody głębokiego uczenia dla zautomatyzowanego systemu monitorowania obszarów miejskich z wykorzystaniem radaru

The Ph.D Thesis , submitted by Mr I. Made Sandhi Wangiyana, has been done in English under supervision of **prof. dr hab. inż. Piotr Samczyńskiego at the Faculty of Electronics and Information Technology, Institute of Electronic Systems , Warsaw University of Technology .**

Structure of the Dissertation

The dissertation consists of eight chapters , each with several sub chapters finished with results and conclusions

The dissertation has a theoretical and empirical character, although the proportions between the two parts are not balanced. The theoretical part (comprising 1, 2, 3, 4 chapters numbers) while the empirical part (number 5 to number 7 and number 8 as conclusions).

Significance of the Addressed Issues

The topic of the research is extremely important, as there is a great development of radar data and the importance of using the data for disasters is essential.
In dissertation Mr Sandhi Wangiyana applies SAR as a source of data for automated analysis the disaster and urban monitoring. In this thesis, deep learning methods were explored for various urban analyses using SAR. The research provided by Mr Wangiyana has related to extraction of building footprints, large event detection from multitemporal data, and LULC classification.

Extreme efforts Mr Wangiyana made to cite and consider results from the literature in order to reach his own conclusions.

In Chapter 1 Mr Wangiyana presents the validity of remote sensing applications in disaster management, presents the knowledge of optical data, gives examples of why optical data could not give enough information in disaster events and describes the advantages of active SAR instruments. In the same chapter Mr Wangiyana presents SAR ability for urban areas especially new growing infrastructures and the advantage of using these data for planners.

Assumptions and Research Objectives

Mr Wangiyana poses three research goals which later he elaborated

1/ It is possible to improve the classification of buildings footprints using the process of augmentation for the limited set of SAR images

2/ It is possible to detect large event changes from multitemporal SAR images applying the autoencoder trained in an unsupervised way

3/ It is possible to do classification of LULC using SAR single polarisation

To achieve these goals, Deep Learning was considered to accomplish generalization.

The aim of the research done by Mr Wangiyana was:

- To evaluate and benchmark of the performance of state-of-the-art neural network architectures used in Computer Vision research on SAR data
- To develop and validate of pre-processing methods for fitting large remote sensing data to reasonable sized neural networks
- To experiment of various data augmentation strategies for radar images
- To experiment of algorithms on various urban landscapes and acquisition modes

To find the directions the PhD student used various publications on Deep Learning for SAR Applications and cited in the literature .

In **Chapter 2** Mr Wangiyana rewiews the SAR theory and image interpretation Detailed description of SAR Acquisition Modes, generation, history of SAR, Range and Azimuth Dimention and Polarimetry. Usual used the horizontal and vertical signals. In all description PhD student refer to the literature. As the SAR data consists of phase and amplitude and in the process of comparison the phase differences of two different images of the same region and the same position but at different time, then the phase changes indicates movement or deformation of the surface. From the literature, Mr Wangiyana noted: "The calculated SAR backscatter is a combination of the radar system's characteristics (frequency, polarization, incidence angle with the characteristics of the surface as roughness, topography, dielectric constant and correlation length" .Then Mr Wangiyana made the explanation of surface roughness, speckle, geometric distortions, and refers to buildings and geometric distortion and what happens when the walls of the buildings face the sensor will be projected to the ground in the direction of the radar and interpretation the effect of the shadow. The same happens with the mountains.

In **Chapter 3** Mr Wangiyana defines Deep Learning (DL) as the subset of Machine Learning (ML) and describes what is Artificial Intelligence and how is set their relationship and cites the reference. Then Mr Wangiyana explains classification task which can be categorized into binary class, multi-class and multi-label. The Deep Learning algorithms can be categorized as supervised or unsupervised depending on learning process. Mr Wangiyana stated that Deep Learning is closely associated with Artificial Neural Network (ANN) consisting of multiple layers where learning is performed automatically building the complex layers. It is stated that the relationship between the data is most not linear and that's why non-linear transformations are offered to neurons. Mr Wangiyana gives the example of the flow from input layer, to hidden layer and output layer when the network is trained using supervised learning ,

It is important to minimize the error: then he explains reducing the error by updating the parameters and minimizing by taking the gradient. Mr Wangiyana states that in supervised classification the cross-entropy is usefull for optimizing the model. **Strongly explains the methodology of Neural Network that will use later.**

Describes also the Convolution layer as a hidden layer that contains several convolution units in a convolutional neural network, which is used for feature extraction. It is important in the 3D input for the feature map. Mr Wangiyana described the advantage of the segmentation models which divide the image into regions established on similarity

Mr Wangiyana discussed the Evaluation metrics where classification accuracy in most cases is evaluated by ground truth but cited the work when such method does not work due to class imbalance and categorized the predictions and errors.

In **Chapter 4** Mr Wangiyana described the Building Damage Assessment (BDA) what is described as the optimal emergency responses after disaster with two subproblems: (1) *building* localization and (2) damage classification. and presents the key findings and opportunities for future research. This is very important approach to select areas with higher concentration of damage. He gives the example of trapped people during the earthquake in Syria and Turkey. Mr Wangiyana gives indication of SAR involvement and describes three involved techniques including combining optical and post -event SAR data. He stressed that the interpretation of damage from SAR should consider the orientation of the building, geometric features of SAR and the surrounding environment. Mr Wangiyana is citing the articles of classification using BDA methods underlying that neural networks are powerful feature extractors. Based on literature Mr Wangiyana summaries that SAR and Deep Learning Methods are used for building unit damage assessment and importance in analysis of disaster to use open source data. The physical property of the surface causes changes in phase and amplitude of the electromagnetic wave changes SAR data and the intensity , phase and polarimetry features are advantage source of information identifying the building changes. It is important to consider intensity and connected to it incidence angle and wave length and dielectric properties and roughness. The L shape pattern and shadow is presented before the disaster while destroyed building showed random patterns from the remaining debris. Mr Wangiyana has cited the literature which describes such configuration.

The difference on value of intensity of SAR images can be used in quantify ground changes caused by disaster. Mr Wangiyana made the discussion that SAR acquisitions before the disaster could not be available and the post acquisition limited to single channel will not bring sufficient information .

<u>That’s why the data-driven approach, such as Neural Networks, is used to train reliable feature extractors for this intricate task.</u>

That’s why the ground change detection applying **Interferometric SAR** by examining the phase has been proposed. The difference of **coherence between pre-event and a post eventSAR is important.**

Mr Wangiyana discussed the **polarization features** sensitive to dielectric constants, physical properties, geometry and orientation of ground targets. Gives citation that the dual polarization as Sentinel 1 VV and VH gives higher accuracy than using one type of polarization. Full polarization (PolSAR) provide information and the volume scattering can be derived from polarimetric decomposition as indicators and polarization coherence.used for characterizing surface roughness and polarimetric orientation angle for describing building orientation. So polarimetry features can be potential for indication damaged and undamaged structures. Features from individual buildings is difficult to identify that’s why it is better to **use block-unit analysis**.

Mr Wangiyana indicated that there **exists openly available dataset which consists of full** polarimetric airborne SAR data with 0.5 spatial resolution covering port Rotterdam This data – set has been the benchmark in SAR and Optical procedures.

Deep Learning Methods are proposed to classify damage using optical images as example is the use of View2 applications.

Using segmentation task, the RescueNet was proposed for joint segmentation and damage Mr Wangiyana stressed that the automating damage assessment lies in speed improvement . The Microsoft Lab proposed a model that is three times faster than the winning solution of View 2. Public dataset takes the role in training deep learning models but most use optical satellite data and as Mr Wangiyana wrote, only a single dataset applying SAR (QuickQuake) is available.

Mr Wangiyana has been investigating different ways of using satellites and different datasets for disaster assessment applications. Important is frequency and resolution of the data. The crucial role are the Sentinel1 A and soon C and D from Copernicus Programme allows fast mapping of damage after disaster. ICEYE is commercial radar satellite of X band (there are nearly 40 satellites, ALOS-2 from Japanese JAXA , with StripMap mode recently released as free for the EarthQuake in Japan. Maxar offers both fresh high-resolution imagery and the world's largest archive for historical analysis of VHR optical data used mainly for disaster events, recently at Turkey-Syria earthquake in 2023. Mr Wangiyana stated existance of, the International Charter on Space and Major Disasters which is a cooperative agreement between the world's major space agencies to pool their remote sensing satellites and archival imagery to aid countries whose people are impacted by natural or man-made disasters. There is no charge to the end users. Exists also the Humanitarian OpenStreetMap Team, but often overestimate destroyed buildings. GlobalBuildingMap dataset covers global areas for temporal coverage between 2018 and 2019 with spatial resolution only 3m. what omits smaller buildings. On line available is Microsoft Building Footprint and Google with spatial resolution of 0,3 - 0,6m respectively.

But what Mr Wangiyana pointed out that it is important the availability of SAR data before the disaster event and after what often data before does not exist. The level of damage is very complex and that's why it is difficult to have details from the satellites. The ImageNet large scale Visual Recognition Challenge dataset is often used to evaluate developed deep learning models.

Mr Wangiyana is concern about Future Directions. The simulating data have been developed applying SAR for urban areas, scientific analysis and georeferencing and may be used for sensor design, algorithm development and training.SAR simulators have been used in military and object detection. Mr Wangiyana draws attention on newly released Building3D dataset for open-source research could be useful for simulating an urban landscape. For the future the post disaster building models can be used for simulating radar signatures from various damaged objects.

Mr Wangiyana recommends to use methods which rely on less labeled data such as Self-Supervised Learning (SSL). The trained model was evaluated and demonstrated generalization capability of SSL methods.

Mr Wangiyana concluded that the lack of pre-event SAR data therefore deep learning methods are among the best solutions and for future research proposed the solutions as: Integrated data collection which should have high quality benchmark dataset; generating SAR simulators and post-disaster building damage models.

In **Chapter 5** the PhD student proposed SAR data augmentation as the solution to the limited SAR data sets comparing to optical data and to improve robustness from SAR specific features and selected augmentation features that improve detection from radar imagery and applied automated methods as Deep Learning using Convolution Neural Network.

Mr Wangiyana cited that small area buildings ex in Asia were undetectable . The models were prforming well in European cities. Unfortunatelly not many datasets with VHR SAR data are available for public usage. Data Augmentation (DA) increases the set of possible data points and increasing generalization. Mr Wangiyana presents the SpaceNet 6 which was dedicated to automatically extract building footprints with computer vision and artificial intelligence (AI) algorithms using a combination of SAR and electro-optical imagery datasets. This openly-licensed dataset features a unique combination of half-meter Synthetic Aperture Radar (SAR) imagery from Capella Space and half-meter optical (EO) imagery from Maxar's WorldView 2 satellite.

Mr Wangiyana described that for training the Building Footprint Extractor algorithm, the HH polarization was used and the augmentation methods is presented. There are pixels belonging to building region and the rest of the pixels. The training and evaluation has been performed and statistics over each image has been done.

Mr Wangiyana describes the **ablation study which** aims to determine the contribution of a component to an AI system by combinations of transformations which were applied to the component.

Mr Wangiyana describes the Geometric Transformation and the requirement of sharpening to improve the edge detection. Also Mr Wangiyana presented different speckle reduction filters to smooth the specle and presented the filtration results on an image.

It was specified that the order of transformation is important when multiple augmentations are combined.

To prove the impact of augmentation method Mr Wangiyana presented the experiment and concluded that the error between training and validation was lower when the augmentation method was used.

Mr Wangiyana presented the experiment of several combinations of positive augmentation methods which were applied to the main training set and evaluated on validation set and stated that applying augmentation increases confidence, and increase in modeling more accurate shape.

In **Chapter 6** Mr Wangiyana proposed the autoencoder to detect large incidents which cause the changes applying multitemporal SAR data of Sentinel1.

The goal is to detect large event changes caused by various types of natural disasters.

To make the identifications of the areas of changes, Mr Wangiyana used pre and post images

Change Detection is one of most important field in Remote Sensing where the disaster assessment could be evaluate by SAR due to penetration through clouds is much better than optical. Increase of quantities of remote sensing data, conventional algorithms began to be replaced by neural networks.

The autoencoder was used to learn representations of SAR data leading to a flood event. It was then used to predict changes from other disaster types by taking the distance of encodings in the space between bitemporal pairs of images as a measure of change.

Mr Wangiyana showed the data collection method and cited the WorldFloods dataset which is a publicly available collection of satellite imagery of historical flood events from several existing databases in "machine-learning ready form" and also databases where the flood extent map was derived is CEMS, providing a catalog of emergency responses in relation to different types of disasters.

The vector data derived through photo-interpretation is used as a reference for observed changes.

The multitemporal SAR data collected over the Area of Interest (AOI) was attached in the vector package. The Sentinel1 were used with spatial resolution of 10m VV& VH . The floods, wildfires, and landslides were considered.

Mr Wangiyana poses the test **"whether the change detection algorithm trained to detect flood events can generalize to other large-scale natural events in different locations.".**

Each event of floods, wildfires, and landslides has two locations.

Mr Wangiyana propose to transform pixel intensity values to present the changes.
Difficulties are natural changes such as vegetation growth, and the presence of SAR speckle, can be challenging to develop the change detection algorithms.

Mr Wangiyana trained autoencoder on five flood locations each with four temporal SAR images. Training aims to minimize the reconstruction loss which is the Mean Squared Error (MSE).
The trained model was evaluated on six locations of three different types of events, utilizing the difference between encoded features from bitemporal pairs to measure the degree of change.

The evaluation for floods was poorer than other events. This was due to a high number of false positives in surrounding agricultural areas, which most likely have a drop in backscatter due to increased moisture after heavy rains.
For wildfires, the burnt areas have lower backscatter in both VH and VV channels
The drop was not consistent throughout the whole labeled burnt area. Some parts had more decreases than others.
Mr Wangiyana stated that the burnt area from wildfires in radar images does not show as clearly as in optical images.
The effect of land movement results in landslides is a prominent change of backscatter from the partial or total removal or modification of vegetation, which displays clear boundaries from unaffected areas.

To Conclude:
Mr Wangiyana proposed the unsupervised approach to detect general large event changes from multitemporal SAR images
The autoencoder was trained to reconstruct pre-event SAR images and learn the underlying representations. The trained autoencoder was used to detect changes from bitemporal SAR pairs by computing the distance between their embeddings.

In **Chapter 7** Mr Wangiyana proposed the analysis of urban density which can be distinguished applying polarimetric SAR data and comparision of single polarization X band

and dual polarization C band. Mr Wangiyana used the Urban Atlas dataset as a reference and used unsupervised clustering and supervised segmentation methods.
Mr Wangiyana came into conclusion that built-up structures induce strong backscatter and can be distinguished well on microwave imagery and urban mapping can be important from radar images. The different scattering of anthropogenic objects - buildings, concrete structures, roads, squares, makes these surfaces distinguishable**.**

In summary, it can be said that Mr **Wangiyana** provides an evaluation of single polarization X-band and dual polarization C-band SAR data for LULC classification in urban areas.

Features derived from the radar intensity data as texture and speckle divergence were used as input.
There are the limitations of these SAR features in relation to the Urban Atlas dataset used as reference
Mr Wangiyana has chosen two cities with diverse topographical structures and various residential, commercial, and industrial buildings: Warsaw and London. He used X and C-band. ICEYE (VV in 9.65 GHz) and Sentinel-1 (VV and VH in 5.4 GHz) were the datasets
The dates of the images were selected to be close to each other and cover the period without vegetation. ICEYE, The SpotLight Extended Area (SLEA) and Strip Map (SM) modes used the Interferometric Wide (IW) mode on Sentinel-1.
Several image features Mr Wangiyana extracted from each SAR data to support the classification of land classes.
In this research, texture features are extracted using GLCM (Gray-Level Co-occurrence Matrix (GLCM)) based on the log intensity SAR image. Texture images derived by GLCM are the result of second-order calculations, meaning they consider the relationship between reference and adjacent pixels.
Mr Wangiyana applied speckle divergence from SAR log-intensity to delineate settlement areas that have the characteristics of bright intensity and high speckle divergence.
It supports to distinguish from natural areas like agricultural fields, shrubland, or forest which often show relatively homogeneous texture.
However, between high density and medium density classes, there is no visible distinction.

Mr Wangiyana prepared **the Workflow in the Methodology of the thesis – preparation of exact applications which is as follows:**

<u>Detailed Datasets preparation</u>:

SAR data preprocessing with needed corrections.

Intensity SAR image calculation.

Training samples preparation according to urban classes' definition.

<u>Main data processing and analysis</u>:

Speckle divergence and texture performance of SAR data;

SAR image classification using supervised and unsupervised approaches;

Evaluation of the accuracy and comparison of the results.

<u>Performed results</u>: two algorithms were compared: unsupervised clustering using K-means and supervised segmentation.

Tiling was performed on the large SAR raster with a tile size of 512 by 512 pixels

The model was trained

Application of Alghoritms

Unsupervised Classification; Supervised Semantic Segmentation

Estimates of the classification performance of the algorithms

Mr Wangiyana discussed the Classification results when two algorithms were compared: unsupervised using K-means and supervised

segmentation using Unet as the neural network architecture

For Vegetation, the Results in C-band are better because of the dual polarization and smoother texture compared to X-band

Mr Wangiyana has concluded and described analysis on different details and polarimetric features from the C and X-band SAR data and stated that **Neural networks consider** not only spectral and textural features, but also geometric and multiscale neighboring information,

Large objects were delineated better in C-band, while X-band radar is more sensitive to small surface roughness.

<u>Mr **Wangiyana presented the comparision** of the the single polarization X-band and dual polarization C-band SAR for LULC classification in urban areas and proved that X-band with higher detail is more suitable for urban analysis despite more SAR features being present in the dual polarization C-band.</u>

<u>The use of Urban Atlas as a reference source is rather limited</u>

<u>The suggestions to incorporat with data augmentation methods could improve its potential for training algorithms for LULC classification using a single polarization SAR image.</u>

In **Chapter 8** Mr Wangiyana concluded the results and performed possibility of future work The aim of the research has been dedicated to verify the use deep learning algorithms to develop a monitoring system for disaster mitigation. The significant changes in the urban landscape can be detected using SAR satellite imagery. The improved spatial resolution can provide input data for the classification and localization of infrastructures. SAR data provide continuous monitoring and could give data at poor weather conditions that follow a disastrous event.

To overcome the problem of limited training data leading to overfitting in supervised learning, Mr Wangiyana investigated the effects of different data enhancement methods on SAR. Pixel-based transformations were not as effective on SAR as on natural color images.

Geometric transformations were shown to be effective in delaying overfitting.

The multitemporal Sentinel-1 images were used to train an autoencoder in an unsupervised manner. The ability to detect general events was demonstrated by the autoencoder, which was trained only on SAR images of flooding events, and was able to detect changes in SAR images of wildfires and landslides.

The neural network takes into account not only spectral and textural features, but also geometric and multi-scale neighbourhood information. Mr Wangiyana has demonstrated it in the LULC classification task, where the importance of different SAR features as input to a classifier was analysed.

Mr Wangiyana stated that despite relying on a single polarisation VHR SAR, the high level of detail provides more features for the identification of man-made structures. The solution was tested in two urban areas with different topographical structures,

In general, the DEEP LEARNING algorithms proposed by Mr Wangiyana demonstrate the feasibility of automated analysis using SAR images. The different urban landscapes and sensor configurations validate the generalization capability of the algorithm.

Evaluation of the Doctoral Dissertation

Scientific Value of the Dissertation and Assessment of the Purposefulness of the Conducted Research

The topic undertaken by Mr Wangiyana is extremely important and highly relevant, especially in the context of recurring changes in infrastructure caused by threats.

A correctly formulated research hypothesis and well-defined research problems allowed Mr Wangiyana to properly establish three main research objectives**.**
In the first part of the thesis Mr Wangiyana described the SAR data, and Deep Learning and on this bases he build his own research.
The extensive literature to which Mr Wangiyana refers is undoubtedly a significant contribution to this work (201 positions), highlighting the researcher's commitment to citing published sources and demonstrating a high level of research excellence
The study focuses on a significant issue related to Deep Learning methods for automated Urban monitoring. This approach aims to explore the feasibility of deep learning algorithms improve the accuracy and efficiency of classification methods by selecting the most relevant features of C and X band.
From a scientific perspective, the thesis demonstrates a high level of research, depth of analysis, and an innovative approach to solving the given problem. The study provides a well-structured and insightful examination of the subject, contributing valuable findings to the field.
The analysis of results, derived from extensive research, is both logical and well-documented. The study presents the outcomes and strong conclusions.

The findings reinforce existing literature while offering novel perspectives on applications of Deep Learning Methods for urban monitoring. In conclusion, this thesis contributes to the growing needs in examining disasters using radar data offering meaningful insights in theoretical and practical advancements. The research done by Mr Wangiyana open avenues for future research which is so important to be continued.

In conclusion, I state that the doctoral dissertation confirms a broad general practical and theoretical knowledge in the field of *Deep Learning Methods for Automated Urban Monitoring System Using Synthetic Aperture Radar* and demonstrates the ability to conduct independent scientific research. Furthermore, it constitutes an original solution to a scientific problem by Mr I Made Sandhi Wangiyana.

Reviewer's concerns

In the thesis there are too much obvious descriptions of SAR, its history, acquisitions etc and it looks that the proportions in the thesis are disturbed.

Can the developed algorithm be applied to other areas? If so , it is a pity that Mr Wangiyana has not conducted and presented the validation with the names of the places,
I would like Mr Wangiyana to present the circumstances when soil moisture is high and how the SAR data will be effected . Also how the whole disturbance will occur applying ALOS data with long wave L.
Could you think of other reference data than Urban Atlas especially not for urban data and if for urban then other?
You wrote that there are the limitations of these SAR features in relation to the Urban Atlas dataset used as reference, what limitations?

Konkluzja

Po analizie wszystkich wymienionych w przedstawionej recenzji uwag wnioskuję o wyróżnienie przedłożonej mi do oceny rozprawy oraz stwierdzam, że rozprawa spełnia warunki określone w Ustawie z dnia 14 marca 2003 r. o stopniach naukowych i tytule naukowym oraz o stopniach i tytule w zakresie sztuki zamieszczonej w Dzienniku Ustaw nr 65 poz. 595 Art. 13.1 i Rozporządzeniu Ministra Edukacji Narodowej i Sportu z dnia 15 stycznia 2004 r. w sprawie szczegółowego trybu przeprowadzania czynności w przewodach doktorskim i habilitacyjnym oraz w postępowaniu o nadanie tytułu profesora zamieszczonego w Dzienniku Ustaw Nr 15 poz. 128. Wnioskuję, zatem o dopuszczenie mgr I Made Sandhi Wangiyana do publicznej obrony tej pracy.

Podpisane elektronicznie przez Katarzyna Danuta Dąbrowska-Zielińska (Certyfikat kwalifikowany) w dniu 2025-03-22.