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Remote measurement of building usable floor area – Algorithms fusion

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ABSTRACT

Rapid changes that are taking place in the urban environment have significant impact on urban growth. Most cities and urban regions all over the world compete to increase resident and visitor satisfaction. The growing requirements and rapidity of introducing new technologies to all aspects of residents' lives force cities and urban regions to implement "smart cities" concepts in their activities. Real estate is one of the principal anthropogenic components of urban environment thus become a subject of thorough multidisciplinary analysis in the field of data requiring spatial information systems. Recent advances in information technology, combined with the increased availability of high-resolution imagery from Earth observation, create an opportunity to use new sources of data that enable to identify, monitor, and solved many of urban environmental problem. The aim of the paper is to elaborate precise, complete and detailed property information with the use of remote sensing observations in a suitable numerical algorithm. The authors concentrate on providing one of the most important, and probably the most lacking, feature describing properties – building usable floor area (BUFA). The solution is elaborated in the form of an automatic algorithm based on machine learning and computer vision technology related to LiDAR (big data), close range images with respect to spatial information systems requirements. The obtained results related to BUFA estimation in comparison to the state-of-the-art results are satisfactory and may increase the reliability of decision-making in investment, fiscal, registration and planning aspects.

1. Introduction

The rapidly expanding urban areas of the world constitute challenge for the 21 st century that requires both new analytic approaches and new sources of data and information (Miller and Small, 2003). Modern management of the urban area is to be considered from many aspects, where one of them, is access to the tailor-made information within the smart cities systems. The Miller and Small (Miller and Small, 2003), Gillanders et al. (Gillanders et al. (2008)) and Zhou et al. (Zhou et al. (2012)) point out that increasing availability of remotely sensed observations and a variety of other geospatial information significantly support the development of new tools and approaches for understanding the urban space. Land cover relate the physical and biological cover over the surface of land, including water, vegetation, bare soil, and/or artificial structures. Land use usually refers to signs of human activities such as agriculture, forestry and building construction (Banzhaf and Hofer, 2008). The structure elements of buildings are one of a scale-dependent of the urban analysis elements (Rashed and Jurgens, 2010). Process of urbanization at the scale of local and regional area effects must be documented, analysed, evaluated and if possible, predicted. This goal can be only achieved by involvement of researchers and stakeholders to cooperating and exchanging knowledge (Longley, 2002; Grimm et al., 2000; Lee and Sasaki, 2018). Indispensable in that scope is defining and monitoring of land-cover and land-use as a part of urban environment with the Urban Remote Sensing technologies. The Urban Remote Sensing (URS) according to Rashed and Jürgens "has proved to be a useful tool for cross-scale urban planning and urban ecological research" recently (Longley, 2002).

Buildings are principal components of urban environment. Sooner or later everyone has contact with buildings that are a place for life, work, investment and relaxation. That is why buildings are part of many decision-making systems related to valuation, taxes, land planning and sustainable development of the areas. However, due to the complex specificity of properties (many functions, influenced by many unstable and stagnant features, unspecified relations and strong behavioural impact), these are very difficult /troublesome components (subject) of the decision-support systems. For this reason information technology is increasingly being utilized in this field (AlZaghrini et al., 2019).

Decision-making systems fed with property (building) information are based on different methods and models. One of them is based on geostatistical analysis which additionally takes into account property

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Table 1
Selected UFA measurement rules.
Source: Own study based on Łuczyński & Kotarba (Zbroś, 2016) and Zbroś (Telega et al., 2002).

Measurement rules	PN-70/B Polish Standards (Poland)	ISO 9836 International Organization for Standardization	GIF Area measurement standard (German)	TEGOVA The European Group of Valuers Associations	BOMA Building Owners and Managers Association	IMPS International property measurement standards
Object from which measurement is made	unplastered walls	plastered walls	dominant portion	wall or window (facade domination rule)	wall or window (depending on facade type)	dominant portion
Measuring height	1 m above floor	at floor level	at dominant portion level	1.5 m above floor	at floor level	at dominant portion level
Construction walls	not included in usable floor area	not included in usable floor area	included in usable floor area	included in usable floor area, if their area is smaller than 1 m^2	not included in usable floor area	not included in usable floor area
Partition walls	not included in usable floor area	not included in usable floor area	included in usable floor area	included in usable floor area	included in usable floor area	included in usable floor area
Headroom- related area reduction	headroom over 2.2 m— area calculated in 100 %; headroom from 1.40 to 2.20 m— area calculated in 50 %; headroom less than 1.40 m— area not calculated at all	area divided into two parts: - part with headroom 1.90 m and more- part with headroom less than 1.90 m	area not reduced but areas with headroom less than 1.52 must be shown separately	none	area not reduced but areas with headroom less than 1.52 must be shown separately	area not reduced but areas with smaller headroom (depending on local law) must be shown separately
Measurement precision	0.01 m	0.01 m	0.01 m	0.01 m	0.01 m	0.01 m
Calculation precision	0.1 m^2	0.1 m^2	0.1 m^2	0.1 m^2	0.1 m^2	0.1 m^2

geographic location or use geographic information systems (GIS) integrated with others (Abbas et al., 2019; Renigier-Bilozor et al., 2019; McCluskey et al., 1997; Renigier-Biłozor et al., 2018). Another approach, currently even more dominant, involves artificial intelligence-based methods, data mining and machine learning in the framework of GeoComputation uses (Zavadskas et al., 2017; Barber, 2017; Park and Bae, 2015; Bello and Verdegay, 2012; McCluskey et al., 2012; Bieda et al., 2019). Even though public authorities in many countries are responsible for running public property information registers, the information provided from them in terms of property analysis seems inadequate or incomplete (Kustra et al., 2019; Benduch, 2017; Christidou and Fountas, 2017). The problem of insufficient property data or unavailability of information on the property market increases uncertainty in the analysis (Renigier-Biłozor et al., 2019, 2017; Yigitcanlar, 2015; Foord, 2013; Yovanof and Hazapis, 2009; Szulwic et al., 2015).

Due to the above the paper proposed new automatic algorithm presented in experimental work related to building usable floor area estimation in the following work structure. First, an explanation of the reasons for looking for a usable floor area estimation new solutions is provided - Section 2. Section 3 presents methods, data, and algorithm methodology of BUFA estimation. Section 4 presents workflow of proposed BUFA estimation algorithm and empirical results obtained on the basis of residential buildings case studies. Finally, Section 5 presents the conclusions and future directions of research.

2. Literature review - property information sources and usable floor area (UFA) determination

Property information sources, if understood as public registers, are considered as parts of land administration systems (LAS) which provide support in general decision making and assist the public administration in the process of fulfilling its statutory duties (Lepkova et al., 2008; Dawidowicz and Źróbek, 2017). According to Dawidowicz and Źróbek (ISO 19152, 2012ISO 19152, 2012), many countries are in the process of integrating Land Information Systems (LIS) in order to develop LAS. This is a consequence of the introduction of the Land Administration Domain Model (LADM) as an International Standard (Kalantari et al., 2015) which forced administration bodies worldwide to adopt this standard into their current processes and cadastral information systems (Manzhynski et al., 2016). Since that time, bridging the gap between LADM and different property information sources began (Kalantari et al., 2013; Zareiforoush et al., 2015).

While a number of studies have concentrated on the use of particular models/method/algorithms with insufficient data (Renigier-Biłozor et al., 2017) in the authors' opinion, attention should be paid to solutions providing appropriate and precise information to feed the models. For this reason, the authors of the paper formulated the following thesis: an automatic algorithm based on mutual technologies and methods fusion: spatial estimation, machine learning, computer vision, fuzzy theory enable crucial information delivery with buildings related data that increase reliability of land information system. In order to solve real world computation problems, a combination of computational techniques is preferred to the exclusive use of single methods (Kara et al., 2018).

One of the key decisions that should be taken into account includes determination of the buildings comparison unit to which the comparison refers (e.g. m^2 of land area, m^2 of building space, m^3 of cubic capacity). The usable floor area of buildings tends to be the most favourable comparison unit in terms of residential property analysis. Generally, the property "usable floor area" (UFA) is understood as the area measured along the internal length of the walls on all floors of the residential rooms intended for permanent residents. Kara et al. (2018) noted that floor area definitions and measurement principles might create dramatic variances in practice, even among terms that have very close definitions. Many countries maintain a national standard for representing the measurements of floor areas in buildings. The national standards generally use similar basis for measuring building floor areas, in fact, areas specified in national standards often have semantic differences (Łuczyński and Kotarba, 2017). There are many detailed regulations concerning the UFA determination/measurement (Table 1).

Even though UFA of buildings is widely used, the access to information concerning this attribute is limited or questionable in terms of its precision. This is caused by the way of information provision. The usable area (in case of direct way of provision) is either declared by building owners (the source of lack of preciseness – conscious/unconscious) or determined with specific algorithms for administrative purposes (if possible) (Zbroś, 2016; Telega et al., 2002; Benduch and Hanus, 2018). Other cases of UFA provision are significantly limited because of the protection of property ownership rights, in other words, there are no other ways of direct building UFA determination. That is why there were rare attempts of usable area determination based on indirect methods. According to Kara et al. sources of areas of property units or parts, such as land registers, building and dwelling registers and architectural projects, generally do not provide explicit information on the procedures, semantics and methods used to compute them. Additionally, national measurement standards more or less use similar basis for measuring floor areas, but semantic differences between various types of areas specified in national standards often found misleading (e.g. measuring a specific floor area in one building using different national standards results in variations up to 30 %) (Łuczyński and Kotarba, 2017).

Analyses of the current state-of-the-art revealed that one attempt of UFA determination was imposed at the administrative level in Polish legal system - Guidelines for general property taxation (Benduch and Hanus, 2018). According to the §20 of the mentioned guidelines, the area of the land components is determined as follows:

- the plane of a multi-storey building (residential, office, etc.) is the product of the building area and the number of storeys (2.5 m, 3.5 m); usable attic is taken as 0.7 storeys, basement as 0.5 storeys: (Eq. 1):

$$PPTN1 = PB{\cdot}LS + PB{\cdot}LA{\cdot}0{,}7 + PB{\cdot}LB{\cdot}0{,}5 \tag{1}$$

where:
P_{PTN1} – estimated UFA of a building,
P_B – building area (surface area of the object),
L_S – number of storeys,
L_A– number of attics,
L_B– number of basements.

- the area of buildings with a different number of storeys is the sum of the products of parts of the building area and the number of storeys in these parts (Benduch and Hanus, 2018) (Eq. 2).

$$P_{PTN2} = \sum_{i=1}^{n} P_{BPi}{\cdot}L_{SPi} \tag{2}$$

where:
P_{PTN2} – estimated UFA of a building,
P_{BPi} – building area parts,
L_{SPi} – number of storeys in building parts.

Benduch and Hanus (He et al., 2017) proposed the concept of estimating UFA of buildings based on cadastral data which tried to “allow for a subtle avoidance of the limitation”. The authors proposed three approaches: simplified, general and detailed. The simplified approach is based on the geometry of objects and the number of storeys (overground and underground) of a building (Eq. 3). The general approach is based on data from the simplified approach and additional information on the material used for the construction of external walls of a building (Eq. 4). The detailed approach is based on data from the general approach and additional information on the number of chambers in a residential building (Eq. 5).

$$P_{UI} = P_B \cdot L_{Kn} + P_{BB} + P_{OZ} \tag{3}$$

$$PUII = (PB \cdot LKn + PBB + POZ) - PSZ \tag{4}$$

$$PUII = PUI - PSZ$$

$$PUIII = (PB \cdot LKn + PBB + POZ) - PSZ - PSW \tag{5}$$

$$PUIII = PUII - PSW$$

where:
P_{UI} – estimated UFA of a building within the simplified approach,
P_{UII} – UFA general approach,
$P_{UII}I$ – UFA detailed approach,
P_B – surface area of the object,
L_{Kn} – number of overground storeys of a building,
P_{BB} – surface area of selected blocks of a building,
P_{OZ} – surface area of selected structures permanently attached to a building,
P_{SW} – surface area of internal walls of a residential building, determined based on the number of chambers in a building,
P_{SZ} – surface area of external walls of a building made of a specific material.

Unfortunately, the proposed methods encountered significant limitations. In order to compare the proposed solution by the authors with the current methods, the authors tried to identify the required and accessible data (provided by property registers) (Table 2).

Other limitations identified by both the authors of the paper and authors of the analysed methods are: controversy with respect to capturing, collecting geometric data of the building and ambiguity of the terminology (e.g. overhang, vestibule, veranda), up-to-dateness of the data contained in the real estate cadastre, impossibility of including rooms of different heights in the calculation process and polysemy of the term of UFA.

In order to decrease the aforementioned limitations in achieving the aim of the paper, an algorithm fusion based on mutual modern technologies and methods combination was proposed.

3. Materials and methods

3.1. The methods and technologies included in BUFA estimation

The main purpose of the algorithm developments was to find the building description model that is optimal in terms of effectiveness, uniqueness and conciseness, giving the possibility of comparing (and differentiating) the examined objects with each other, with respect to the saved entities of the sample models. Hence, the algorithm assumed a gradual (stepwise data enrichment) transition from measurement data, from various sources, to a simplified model of the building

Table 2
Required and accessible data.
Source: Own study basis on property registers.

	PTN_1	PTN_2	P_{UI}	P_{UII}	P_{UIII}
Building area / building parts (blocks) area - P_B, P_{BPi}, P_{BB}, P_{OZ}	+	+	+	+	+
Number of storeys / Number of storeys in building parts (blocks) – L_S, L_{SPi}	+	+	+	+	+
Number of attics – L_A	+/-	+/-	–	–	–
Number of basements – L_B	+/-	+/-	–	–	–
Surface area of external walls	–	–	–	+	+
Number of chambers in the building (for internal walls area determination)	–	–	–	–	+

+ Required data.
-Unavailable data.
+/-Available data of poor quality (certain mistakes).

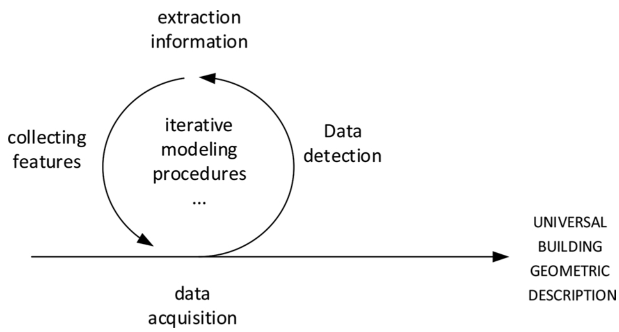


Fig. 1. Iterative collection and processing of measurement data and their derivatives to obtain a final description of the building.
Source: Own elaboration.

containing the unique values of its features.

Considering the need to increase the efficiency of analyses and the inability to implement the indicated steps using only one of the available data sets, it required different methods and the sequential and iteration use of their results (Fig. 1).

In the presented algorithms fusion, the several approaches and technologies in the framework of spatial estimation, machine learning, computer vision, fuzzy theory use were applied in order to solve crucial technical problems in the BUFA estimation procedure: detection of roof planes; doors and windows detection on the building facade; identification of a similar group of properties to the investigated house. For the purposes of the paper analyses the calculation of the components building usable floor area (possible to consider) was based on PN-70/B Polish Standards (Poland).

All described algorithms were done by own developed application in python environment.

The first problem was to determine the geometrical characteristics of the building's roof: its shape in 3D and dimensions. Typical registers (publicly available) do not contain such information or are contained in a complex form of numerical architectural design. The data should therefore be obtained from other sources. Fast and accurate acquisition of spatial data characterized by time coherence describing a large area of land requires the use of modern tools for remote data acquisition. Remote solutions enable to among others presentation of land surface, for example Pacific Catastrophe Risk Assessment and Financing Initiative (PCRAFI) used satellite imagery of different resolution and vintage and validated with the aid of some ground truthing, virtual truthing using high-resolution imagery of more recent vintage and other internet resources, agriculture census, and other ancillary data to developing of land use/land cover maps (Banzhaf and Hofer, 2008). The authors proposed the use of Airborne Laser Scanning (ALS) technology. Its growing popularity (there are also solutions based on unmanned aerial vehicle (UAV) data – competitive from economic point of view) indicates that it will be a generally available solution in the near future. LiDAR is a remote sensing technology that collects geometric and geographic information from targets on the earth’s surface (both on distance to the ground and spatial direction measurement) in the form of point clouds (Hill et al., 2000). This method has been used for a wide range of applications in order to increase in procedure data analysis, e.g. high-resolution topographic mapping (Zhao et al., 2008), 3D surface modeling (Polat et al., 2015; Chen et al., 2012), infrastructure and biomass studies (Doneus et al., 2013), archaeological sites detecting (Rodrigues et al., 2011), remote monitoring of measured objects (Puente et al., 2014), and object detection (Díaz-Vilariño et al., 2015; Burdziakowski and Tysiac, 2019).The only problem that arises with the use of LiDAR big data is the clustering of measurement results to replace independent observations of spatial points with their coherent geometric model - parameterized geometric primitives (segments, triangles, polygons and other complex 3D objects) (Ossowski et al., 2019; Janowski, 2018). In this work, LiDAR data filtration to describe roof geometry was carried out using the modified Msplit estimation (Błaszczak-Bąk et al., 2015; Rapiński and Janowski, 2013; Zienkiewicz, 2014; Wiśniewski, 2010; Gadelmawla, 2017) considered as spatial estimation.

The necessity of detailed building's structural characteristics information collections in conjunction with the assumption of time and equipment resources reduction implied the use of digital images of the assessed object. The acquired digital images of facades with a method other than close range photogrammetry defined as a method for remote measurement object located within approximately 300 m (cost reduction) was also indicated. Such images are characterized by a lack of metrics, in contradiction to typical photogrammetric images products. Due to the lack of image calibration (chromatic and geometric) and analysis of only flat elements in the images, it was assumed that the use of projective transformation (commonly used in photogrammetry tasks especially by computer vision approaches) would be sufficient to assemble metric data of the building model (from previous stage) with the facade representation found in the images. Measurement methods based on photogrammetry and image processing have found application in numerous diverse fields, especially when immediate and accurate results required (Corrêa Alegria and Cruz Serra, 2000; Zheng et al., 2016; Ziółkowski and Niedostatkiewicz, 2019).

The indication in the raster or 3D data of the elements with general geometric characteristics (shape or dimension) is insufficient in the presented synergistic concept of the assessment of BUFA. It assumes the necessity to confirm the existence of elements with specific semantics (context) on the images. This may include traditional statistical methods and machine learning (Tizghadam et al., 2019) and learn the latent patterns of historical data to model the behaviour of a system and to respond accordingly in order to automate the analytical model building (Pawlak, 1982). The advantage of this method is the ability to analyse large resources of complex data, draw conclusions – also from predictive analyses – that are out of reach of the human mind (Park and Bae, 2015).

The next important issue concerned selection (indication) of similar (representative) properties as the investigated buildings. The practical problem of data exploration in geoscience results mainly from the non-homogeneity of real estate (no two buildings are identical). One of methods that is efficient in this case study area is a method based on fuzzy logic and rough set theory. Rough set theory, formulated by the Polish mathematician Zdzisław Pawlak (Janowski et al., 2018), is applied to process imprecise, vague and uncertain knowledge in data analyses. The above features are characteristic of property information and they have to be taken into account when "vague" decisions are made in the area of buildings analyses. Due to this fact, advanced data mining methods were implemented based on fuzzy logic and rough set theory related to manners and procedures of designating similarities (indiscernibility) of buildings. In this case, a causal relationship between features expressed by the physical characteristics are definitely more imprecise, vague and fuzzy.

The presented methodology of BUFA estimation was explained in detail based on the example of the particular case studies of residential buildings located in Olsztyn city area (South-Eastern part of Poland).

3.2. Data

In order to conduct calculation according to the proposed algorithm, diverse data from different sources had to be collected. The necessary data include objects (used for particular stages within the proposed algorithm) and related features (describing particular buildings). The main groups of objects were imposed by the key stages of the algorithm procedure presented in the following chapters. The mentioned groups of objects include:

1 non-metric images of facades with georeference tags – the position

of origin of 3D camera coordinate system and focal length direction to be perpendicular to particular facades was assumed (provided by own or public resources) – the authors obtained 1,240 images (objects) with resolution 4032 × 1960 pixels, 24 Bits colour depth for the identification of the following features: windows, doors.
2 building architecture projects (provided by the project's architecture agency and valuers) – the author obtained 50 projects (buildings) for the following feature identification: number of floors, total area of the building, built-up area, height of the building and roof, roof shape (represented by dictionary type); stored in RDBMS.
3 property transaction databases (valuers' transactions) – the authors obtained 37 transactions (buildings) for the identification of the following features: number of floors, total area of building, built-up area; stored in RDBMS.
4 single family buildings – the authors obtained information on 108 houses (residential buildings), the information included 3D laser point clouds for identification of the following features: height of the building, shape of the roof; stored in RDBMS (with spatial extension).
5 build-up area – 108 geometric polygons records of property build up area obtained from property registry (land and building); stored in RDBMS (with spatial extension).

Such data enable an empirical study to be conducted of the BUFA estimation and verification of the effectiveness of the developed algorithm.

3.3. The methodology of BUFA estimation algorithm

The elaborated algorithm based on the example of single-family buildings BUFA estimation consists of three main stages (algorithms). All of the them were described and verified separately.

The first main step assumed elaboration of the 3D model of a house hull that consists of the building dimensions crucial for BUFA estimation. This step was elaborated within the particular stages. First of them are the analyses assumed combining data from two sources of information: a property registry (land and building) and LiDAR (big data) (Fig. 2)

From the property registry, the two kinds of data were taken: build-up area - S and building location – L_s (polygon coordinates) which occurred as certain information and usually exist as precise data. From the LiDAR, a 3D point cloud of a terrain digital elevation model (DEM) was obtained. At this stage, it should be noted that there is a problem with proper spatial resolution of LiDAR data (provided by ALS available as a public data). In Poland, there is public register of the IT System of Country Protection against extraordinary threats (ISOK) consisting of digital elevation model (DEM) in a point cloud form with a standard I – 4 points/m^2 spatial resolution for most of the country that was acquired within the period of 2010–2015 with varying accuracy of 4–12 points per m2. This is not an acceptable resolution for the presented calculations. Due to this fact, the authors used LiDAR data with 40 points/m^2 resolution obtained from the Vimap Ltd company acquired for the purposes of particular orders.

After obtaining the cloud points, the spatial separation of the data was conducted. In this stage, geometric queries based on spatial (geometry/geography) data for getting its subsets by buffer zones, contains, symmetric differences, covers functions were used based on build-up area. As a result of this stage, the points belonging to the roof of the

Fig. 2. Selecting LiDAR points belonging to the roof.
Source: own elaboration.

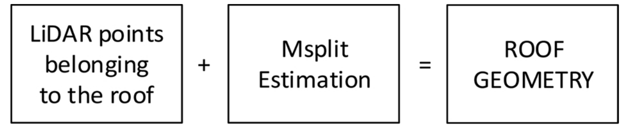


Fig. 3. Roof geometry determination.
Source: own elaboration.

analysed building - D_{LR} - were detected.

After that, the points belonging to the particular q planes of roof were determined using M-split estimation as spatial geometry estimation (the method that enabled separating (clustering) the dataset of points belonging to certain roof planes - D_{LRi}, $i \in 1...q$) (Fig. 3). The slopes and areas of all planes of roof P_i ($i \in 1...q$) were then calculated. The roof planes were estimated using normal vectors for particular planes of analysed roofs.

The assumption of the Msplit estimation (robust estimation) is the existence of n observations (the observation of the position of belonging points) having mixed q random variables (q different roof slopes) of Eq. 6:

$$E\{l\}_1 = \boldsymbol{a}_{(1)}\boldsymbol{X}_{(1)}, ;E\{l_i\}_q = \boldsymbol{a}_{(\boldsymbol{q})}\boldsymbol{X}_{(\boldsymbol{q})} \tag{6}$$

where:

$\boldsymbol{a}$ – vectors of known coefficient values,

X – vectors of unknown parameters q random variables.

Each of the observations (information on the points' location) includes the potential opportunity to belong to one of the defined functional models (roof planes) of Eq. 7:

$$l = E\{l\} + v = \boldsymbol{aX} + v \tag{7}$$

Thus, a set of competing solutions in Msplit can be written as Eq. 8:

$$l = \boldsymbol{aX} + v \rightarrow split \rightarrow \begin{cases} l = \boldsymbol{a}_{(1)}\boldsymbol{X}_{(1)} + v_{(1)} \\ \vdots \\ l = \boldsymbol{a}_{(\boldsymbol{q})}\boldsymbol{X}_{(\boldsymbol{q})} + v_{(q)} \end{cases} \tag{8}$$

for each of n observed points. The purpose of the Msplit estimation is to find the parameters of X sets describing q functional models. The general functional model was the equation of the plane. For the q roof plane, the q definition of the functional models of Eq. 9. was kept:

$$A_i x + B_i y + C_i z + D_i = 0, \ i \in 1...q \tag{9}$$

As a result of solving the Msplit estimating equation from the set of ALS points describing the roof space of the building, the q roof plane was extracted and the edges were found and constructed using alpha-shape (Edelsbrunner, 1995; Yang et al., 2011) flat figures located in 3D space.

This allowed the development of the 3D roof model and the 3D model of the house hull - H_H. Due to this, the first step allowed obtaining the particular necessary dimensions: building height, dimensions and shape of the roof, building volume and roof volume (Fig. 4).

The final result of this stage was the calculation of the range of estimated total area with a floating (i.e. the height of particular floors was not precisely determined) floor solution (Fig.5).

The second stage of the initial step assumed the calculation of the estimated total building area with fixed (detected) floor heights. This stage relied on merging (synergy) vectors (result of 1 step – wireframe of 3D model of house hull) H_h and rasters (images contain visualisation of house facade I_i, $i \in 1...$ No. of facades). At the start, all acquired image

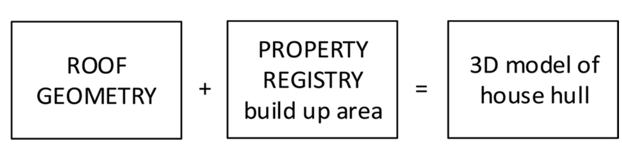


Fig. 4. 3D model of the house hull determination.
Source: own elaboration.

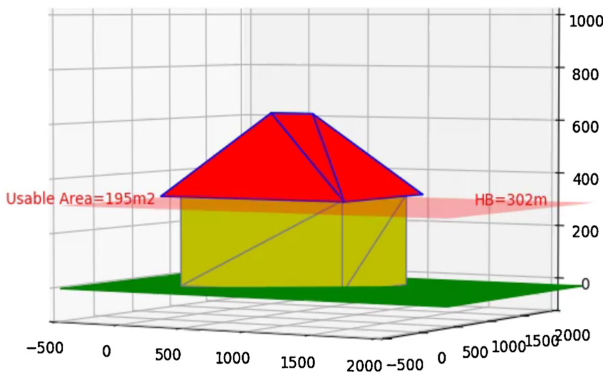


Fig. 5. 3D model of the house hull with floating floor solution.
Source: own elaboration.

facades of the building required a chromatic correction process to improve image quality according to boundary captured object interpretation. In the next step, projective transformation of 2D images to a 3D house hull model was performed (semi-automatic spot detection of homologous in vector and raster model was based on the detection of the longest edges and their intersections in both models). The projective transformation (recognized as well as plane-to-plane projection) was necessary for obtaining metric information about facade objects laid onto non-metric images by adjustment of particular coplanar elements both on the image and house facade of the 3D model.

The crucial purpose of the following step was the context recognition of facade elements (especially doors and windows) on images with metric information added. Therefore, using classic computer vision edge detection operator - Canny (Gao et al., 2010; Freeman, 1961) and Freeman (Shi and Cheung, 2006) chain code and simplification of a vector line object (Ehsani et al., 2018), the rectangular shapes were indicated. This was necessary since many other elements (not only doors or windows) founded on the facade can have a rectangular shape, e.g. ornaments or items. Reliable and efficient labelling/classification is possible using machine learning technology. In this case, the YOLO algorithm (Redmon and Farhadi, 2018, 2017; Gordon et al., 2018; Rastegari et al., 2016; Redmon et al., 2016; Redmon and Angelova, 2015; Komorowski et al., 1999) frameworks were pre-tested by using a training dataset of 1240 images of doors and windows separately using machine learning (semi-supervised learning was used). This enabled the validation process to reliably estimate the object detection. The correct object detection (good recognition) equalled on average 67 % for doors and 72 % for windows. The interpretation of acquired results means that approximately 7 out of 10 doors/windows were detected in a proper way (Fig. 6).

The purpose of the stage was to estimate the height of particular floors on the basis of size and height of facade doors and windows. The occurrence of particular doors and windows at a particular height of the facade (thanks to adding metric information to the images in previous step) enabled the number of usable floors to be assumed. The level of the floor plane was assumed based on height of lowest edge of the door or assumed distance from lowest edge of windows to the potential floor (Fig. 7).

In the third step the main aim was the determination of the building construction area indicator (BCAI). The BCAI includes the area of walls (their thickness) and other common construction elements, e.g. pillars in the house. The crucial stage in this algorithm was the selection of the databases that can be the basis for the indication of the building construction area pattern of similar properties to the investigated property. In this case, two kinds of databases were combined: databases fed by the valuers (with empirical measures taken during building inspection necessary for the valuation procedure) and catalogues of building architecture projects (due to the diverse presentations of buildings with precise dimensions of building components) (Fig. 7). The combination of these two databases was necessary due to the wide range of building development periods (age of the house) and architectural styles. The second stage in this step was the indication of variables (number of floors - with usable character; total area of building; build-up area; height of building and roof; roof shape and other factors, if necessary) that exist in both databases and are crucial from an architectural point of view. In both databases, the calculation of building construction area for particular properties was indicated (Fig. 8).

The next step assumed the selection of the most similar properties to the analysed one. Due to the fact that no two properties are identical, combined with information uncertainty, imprecision, measurement errors and the unavailability of certain types of information, a precise (zero - one) indication of similar properties (buildings in this research) is difficult or even impossible. In view of the above, the authors have proposed the application of **fuzzy** theory and rough set methods (RST) (Janowski et al., 2018; Renigier-Biłozor and Biłozor, 2009; Rapinski et al., 2011; Jina et al., 2014; Stefanowski and Tsoukias, 2000) to select a group of similar building (Fig.8).

In this particular case, the building features were divided into conditional (measures of the building) and decisional (building construction area) sets. Determination of decision rules can be written in the form of a conditional segment (if… then…), and it can be regarded as a decision rule. There are two general types of decisional rules. One of them is "exact decisional or deterministic rule," where the decisional set contains the conditional attributes with quality and accuracy of approximation equal to 1. The second rule is the "approximate decisional rule," in which the decisional set contains the conditional attributes with quality and accuracy of approximation lower than 1 but higher than 0 concerning vaguer, fuzzy relations. In this case, a causal relationship between features expressed by the physical characteristics are definitely more imprecise, vague and fuzzy. The application of value tolerance relation (Stefanowski and Tsoukias, 2000) to the conventional rough set theory based on a crisp indiscernibility relation, a more flexible way to deal with the indiscernibility relation was obtained with a better match to the property analysis. In order to select buildings that are similar to the analysed "valued tolerance relation" (VTR) (Stefanowski and Tsoukias, 2000), conditional variables were applied to according to Eq. 10:

$$R_j(x,\ y) = \frac{\max(0;\ min(c_j(x),\ c_j(y)) + k - max(c_j(x),\ c_j(y)))}{k} \tag{10}$$

where:

$R_j(x,y)$ - relation between objects (building) with a result of membership function [0,1],

x,y – identification of building,

c_j – function of the j attribute selection from a given house,

k - threshold for the similar features set, allows objects to be considered indiscernible despite not having identical values; that is standard deviation.

The results produced by the valued tolerance relation matrix of conditional attributes were summed up and the sum was determined based on the below Eq. 11:

$$R(x,\ p_i) = \sum_{j=1}^{n} R_j(x,\ p_i) \tag{11}$$

where:

p_i –building / object which is a candidate to a given similar group (indiscernible).

Assuming that W_x is the collection of all similar (indiscernible) buildings to x, its contents can be described as fulfilment of the following condition (Eq. 12,13):

$$p \in W_x \Longleftrightarrow T(R(x,\ p)) = TRUE \tag{12}$$

$$P = p_{1\,,}\, p_2,\ p_3,\ \dots p_m \tag{13}$$

This means that the set of W_x (a set of similar buildings to x) consists

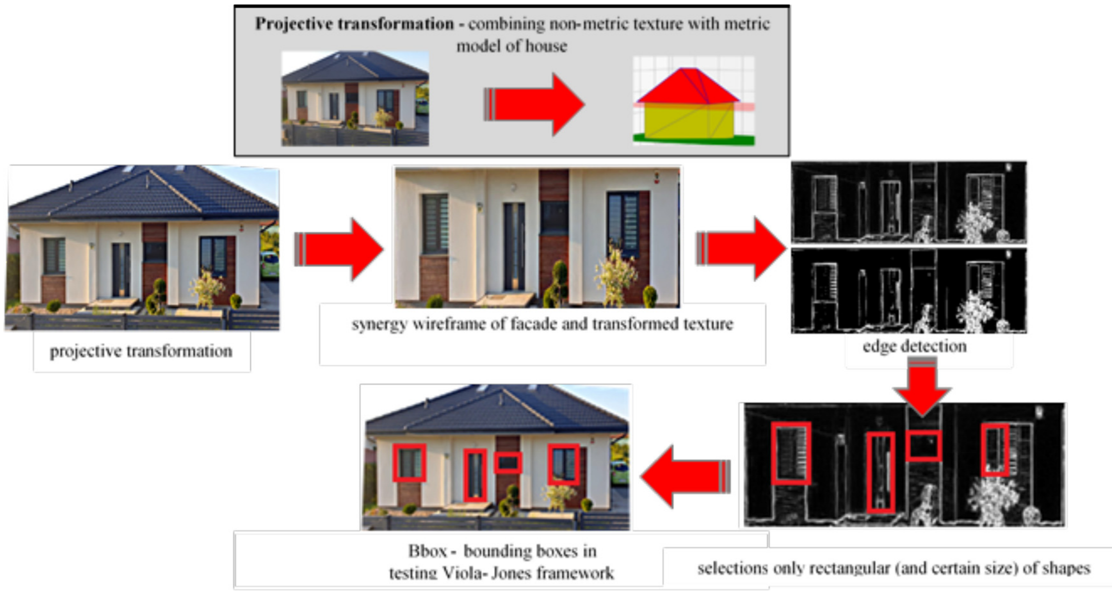


Fig. 6. Second step of BUFA estimation algorithm – detection of height and number of floors and windows.
Source: own elaboration.

only of pi from the *P* set, which satisfies the condition defined as a function of the tolerance *T*. The degrees of indiscernibility were determined at a given level of similarity for sets in decision subgroups. In effect, classes of indiscernibility were determined, taking into account 95 % of similarity due to the fact of specificity of the building data that were described above. In this stage, Eq. 14 on the toleration function is as follows:

$$T\ (R) = TRUE\ \Leftrightarrow\ R > 0.95\max IND_i(B,\ d) \tag{14}$$

This enabled several buildings similar (indiscernible) to investigated building to be selected. The further step in this stage assumed calculation of the indicator of building construction area leading to correction of the building total area - indicated from second step of the algorithm. In this case, the average of building construction area derived from selected houses (considered as similar/indiscernible from analysed building point of view) was calculated.

4. Results and discussion

4.1. The workflow of the proposed BUFA estimation algorithm - single-family buildings example

The algorithm assumed an universal approach, taking into account the common architectural shape (hull) of European residential buildings, which enabled elaboration of the general Formula 15 for BUFA calculation. The explanation of the Eq.15 was presented in the form of a subtask list of programming process and their flowchart. The specific measure conditions based on Polish directives were taken into account to verify the efficiency of the proposed algorithm.

$$BUFA_e = \sum_{k=1}^{m} UA_e(1 - BCAI) = \sum_{k=1}^{m} (\sum_{i=1}^{n} A\ (sec_i^c)\bullet v_i)(1 - BCAI) \tag{15}$$

where:

$BUFA_e$ - building usable floor area of house,

m - number of floors,

UA_e - usable area including construction area,

$BCAI$ - building construction area indicator,

sec_i - horizontal section of house hull for fixed height of house,

$sec_i^c = \mathrm{sec_i} - (\mathrm{sec_i} \cap \mathrm{sec_{i+1}})$ for i∈ 1… n− 1 and $\mathrm{sec_n^c} = \mathrm{sec_n}$ corrected horizontal section,

$A(sec_i^c)$ – area of corrected horizontal section,

v_i – coefficient including rules of usable area determination connected with height of ceiling indicated by $\mathrm{sec_i}$, n – number of defined (domestic standards) of areas with different heights on the floor.

The specific measure conditions based on selected directive (see Table 1) were taken into account to verify the efficiency of the proposed algorithm (Fig. 9).

The subtask list of programming process to calculate the usable floor area:

1 Initial steps:
  1a: determination of the spatial range and location.
- S: built up area,
- L_S: polygon coordinates,
- L_{S3D}: prism developed on the L_S base, 1b: initialization of the LiDAR cloud points dataset;
- D_L: cloud points set,

2 initialization of D_L filtration limited to the L_S range,
- $D_{LR} = L_{S3D} \square D_L$; set of points belonging to the roof,

3 splitting D_{LR} for the separate set points of q roof planes $D_{LR\text{-}i}$ for i∈ 1. .q,
- $D_{LR} = \sum_{i=1}^{q} D_{LR-i}$, q planes P_i for $i \in 1..q$ equation determination using LSM (least square method) based on $D_{LR\text{-}i}$ for $i \in 1..q$ with the goal of minimizing function G from the Eq. 16 below for every P_i

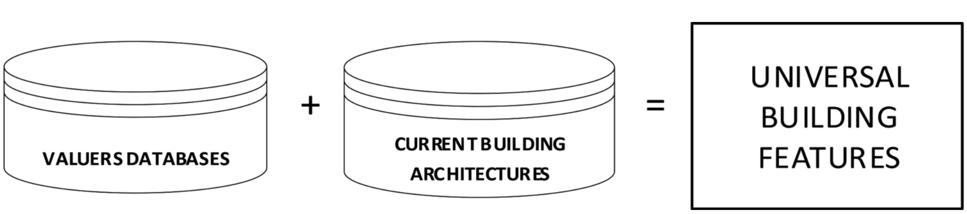


Fig. 7. Universal building features determination.
Source: own elaboration.

Fig. 8. Building construction area indication. Source: own elaboration.

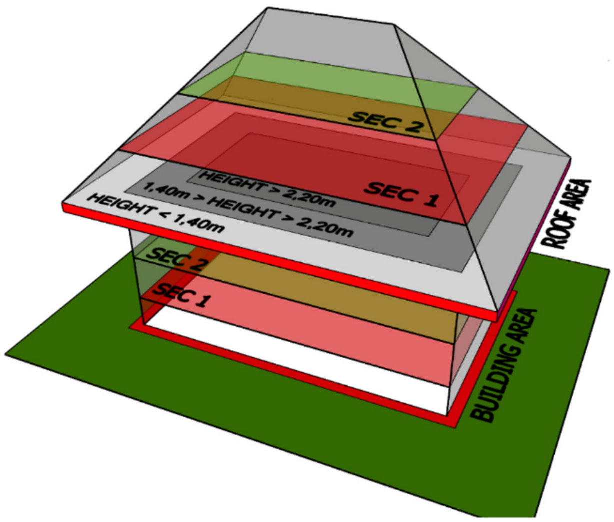


Fig. 9. Model of single-family building visualization – components of Eq. 15. Source: own elaboration.

plane:

$$G_q(A,B,C) = \sum_{j \in D_{LR-q}} [(Ax_j + By_j + C) - z_j]^2 \rightarrow (0,0,0) = \nabla G_q$$
$$= 2 \sum_{j \in D_{LR-q}} [(Ax_j + By_j + C) - z_j](x_j, y_j, z_j) \tag{16}$$

4 roof edges R_{e_i} for $i \in 1..m$, estimated by 3D line equation determination defined as the intersection of compared planes limited to L_{S3D};

5 determination of the house hull HH based on LS and R_{e_i} for $i \in 1..m$,

6 8 image edge detection and facade polygon determination,

7 combining images and H_H data using projective transformation. The result is a set of metric images I_i for $i \in 1..No\ of\ house\ facades$,

8 detection of window and door sets (sets of 3D polygons);

- d_i doors for $i \in 1..j$,
- w_i windows for $i \in 1..j$,

9 division of windows and doors for indication of the particular rows – number of floors – *NF,*

10 indication of the height of particular floors h_f for $f \in 1...NF$, based on height of lowest edge the every row,

11 creation of heights H_{vp1}, H_{vp2} of the virtual floating horizontal planes V_{p1}, V_{p2} related to the defined height of h_f according to chosen principles determined by the aim (e.g. in the Polish case, the usable area calculation rules assume $H_{vp1} = h_f + 1.40m$, $H_{vp2} = h_f + 2.20m$ which indicates the calculation of usable area on the height of floors from 1.40 m to 2.20 m equal 50 % and above 2.20 m equal 100 %),

12 conduction of sections sec_1, sec_2 planes V_{p1}, V_{p2} with H_H *and calculation of their areas,*

13 calculation of the estimated usable area UA_e for particulars using sec_1 and sec_2 (Eq. 17):

$$UA_e = A(sec_2) + A(sec_1 - (sec_1 \square sec_2))/2 \tag{17}$$

14 indication of the building construction area indicator BCAI obtained from most similar buildings developed on rough set theory and data mining technologies,

15 calculation of the final estimated building usable floor area: $BUFA_e = UA_e \cdot (1\text{-}BCAI)$.

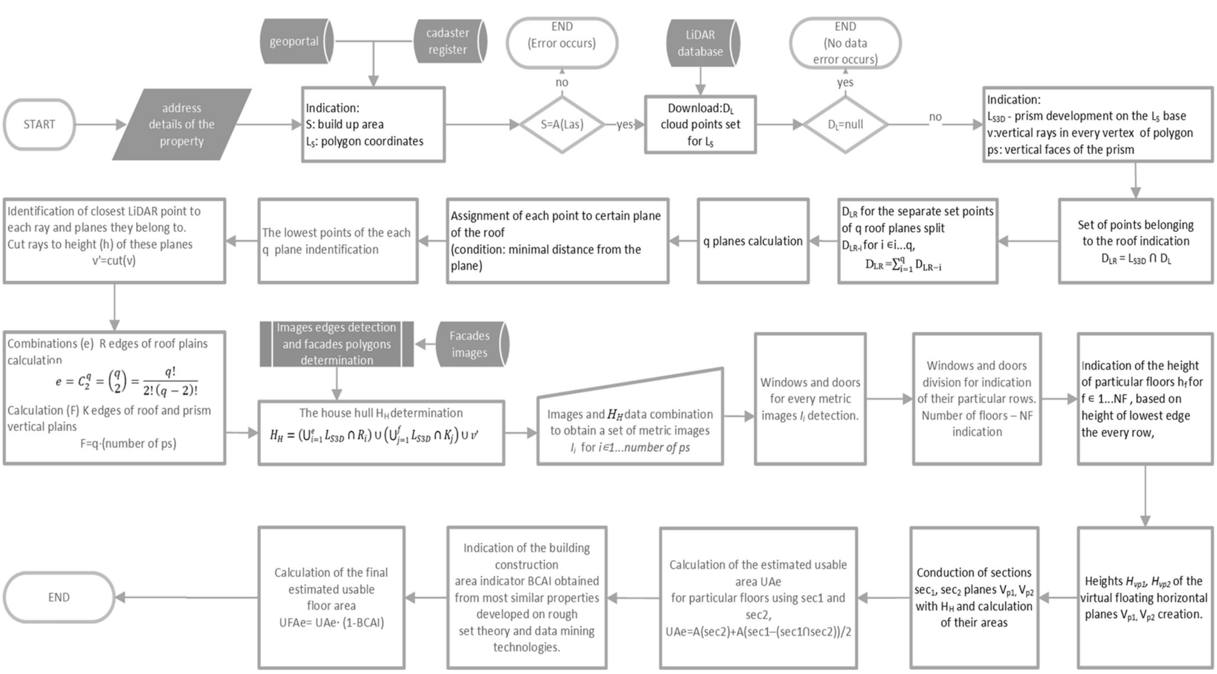


Diagram 1. Flowchart of the BUFA estimation. Source: own elaboration.

FIRST CASE

a residential building of an ordinary (simple) form from an architectural point of view:

- a two-storey building with a usable attic with no basement and a hipped roof
- the actual usable area (according to architectural project) of the building is 126.25 m^2
- the built-up area (according to the property register) is 128 m^2

NF	Number of floors/storeys = 2 (computer vision technology and machine learning used for door and window location
h_{f2}	3.20 m (computer vision technology and machine learning used for finding the doors and windows' lowest edges on a particular storey)
UA_e	174.53 m^2 calculated with defined h_{f2} and with the use of assumptions $H_{vp1}= h_f+1.40$ m, $H_{vp1}=h_f+2.20$ m, obtained from Synergy Geometric Data (SGD)
BCAI	0.23

Estimated building usable floor area from the proposed algorithm BUFA $_e$ =174.53 m^2 · (1-0.23) = 134.39 m^2

Taking into account the actual usable area (126.25 m^2), the difference between it and the estimated BUFA was 6%.

Fig. 10. First case.
Source: own elaboration.

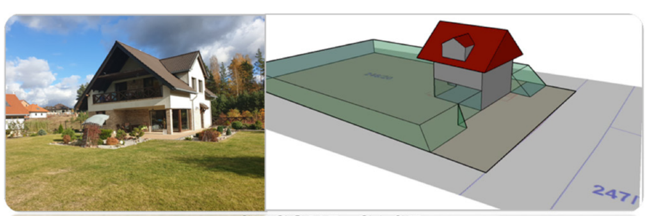
For greater comprehensibility and clarification, the assumed algorithm was presented in the form of a flowchart (Diagram 1). The presented algorithm enabled calculation adjustment to the investigated residential building.

4.2. Discussion and empirical verification of the elaborated algorithm

The developed algorithm was validated on the basis of particular case studies. Two of them were described in detail below (Figs. 10 and 11).

The other algorithm-validating examples are presented in Table 3. The buildings presented in the table are representatives selected from homogenous groups. The groups were elaborated using cluster analysis (Fig. 12) according to features of the building (architectural shape, no of floors, usable attic, geometry of roof etc.) from a set of 108 properties.

The selection within obtained groups was based on the lowest accuracy of BUFA estimation. The tree diagram (Fig. 12) indicated the nine homogeneous groups of buildings indicated from the *k* threshold value 7. The value of the *k* threshold was assumed on the basis of the junction distance. Within the value of 7 (junction distance), the threshold enabled division into an optimal number of comparable groups. In order to present the differences between actual and estimated (according to the proposed algorithm) BUFA, a box chart was



SECOND CASE

a residential building of a more complex form from an architectural shape point of view

- a three-storey building with usable attic with a basement and gable roof
- The actual usable area (according to architectural project) of the building is 180.83 m^2
- the built-up area (according to the property register) is 101.00 m^2.

The pseudo-code and Formula 15 were used in order to calculate the usable area of the building. The following components were obtained from an automatic algorithm dedicated to residential house BUFA calculation

NF	Number of floors/storeys = 3 (computer vision technology and machine learning used for door and window location
h_{f2}	3.16 m (computer vision technology and machine learning used for finding the doors and windows' lowest edges on a particular storey)
UA_e	261.21 m^2 calculated with defined h_{f2} and with the use of assumptions $H_{vp1}= h_f+1.40$ m, $H_{vp1}=h_f+2.20$ m, obtained from Synergy Geometric Data (SGD)
BCAI	0.24

Estimated usable floor area from the proposed algorithm =261.21 m^2 · (1-0.24) = 198.52 m^2.

Taking into account the actual usable area (180.83 m^2), the difference between it and estimated BUFA was 9%.

Fig. 11. Second case.
Source: own elaboration.

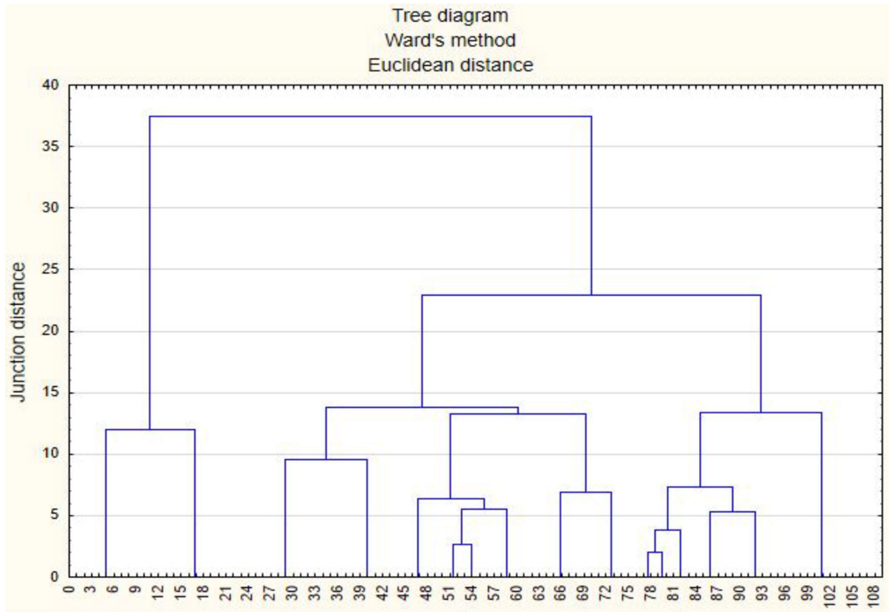


Fig. 12. Tree diagram of buildings homogenous groups.
Source: own study.

elaborated.

In Fig. 13, a graphical depiction of nine homogenous groups and numerical data through their quartiles is presented. The properties of the lowest accuracy of BUFA estimation were indicated by the upper whiskers (Fig. 13).

The obtained lowest accuracies of BUFA estimation were presented in Table 3. The selected results enable presenting the worst possible scenario of an applied algorithm on the set of 108 buildings Table 3.

The results of BUFA calculation, in comparison to the current state of art (guidelines for general property taxation (see Eq. 1) and UFA estimation within the simplified approach (see Eq. 3)), are far more precise. The comparison to other described state of art solutions (general approach – Eq. 4 and detailed approach – Eq. 5) was not possible because of the lack of required data: surface area of external walls and number of chambers in the building (Table 3). The comparison (BUFA calculation and current state of art methods) was made on the example of 19 buildings (Fig. 14).

The differences in results within the two current state of the art methods (presented in Fig. 14) are mainly caused, as has been noted, by the lack of consistent property (building) descriptions in the cadastre. In other words, the data provided by public registers is false or inaccurate. For example, the difference in results for building number 7 is caused by the fact that the property register did not indicate the usable attic appearance. A similar mistake caused by the quality of data was identified in cases 2, 3 and 4. In these cases, the differences were made by a lack of existing underground storey indication. The gross errors in comparison of the current state of the art methods and actual BUFA were caused by polysemy of the term of particular space/room in houses.

5. Summary and conclusion

The analyses indicated that elaborated use of advanced solutions for UFA determination in the form of a coherent system allows obtaining

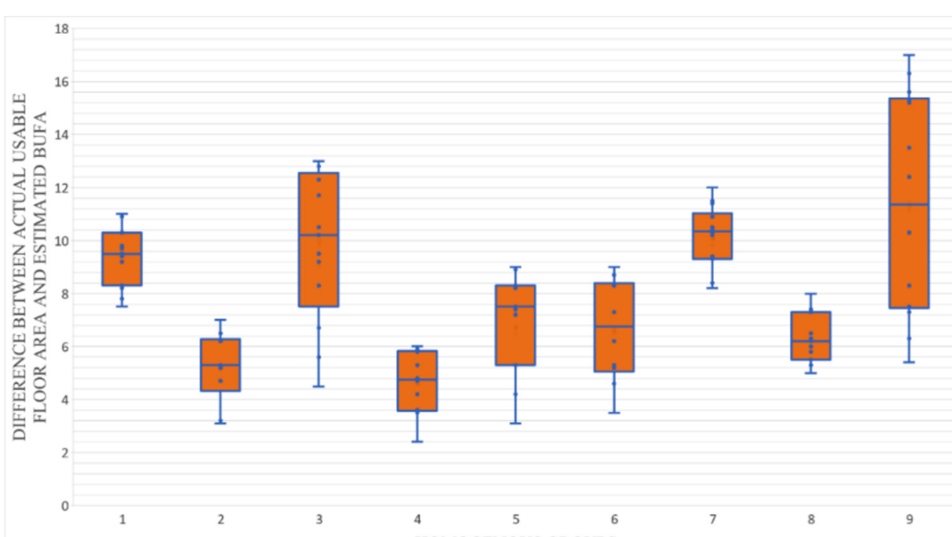


Fig. 13. Range of differences in BUFA determination within homogenous groups of buildings.
Source: own study.

Table 3
Algorithm validating results examples – case studies.
Source: own study.

No	Description of residential buildings	Actual usable area from own measurement	Estimated BUFA from the advanced automatic algorithm	Difference between actual usable area and the estimated BUFA
1	residential building of more complex form from architectural shape point of view; two floors building with usable attic and gable roof	$117.49\ m^2$	$130.41\ m^2$	11%
2	residential building of ordinary architectural shape; one storey building with gable roof	$165.12\ m^2$	$176.69\ m^2$	7%
3	residential building of complex form the architectural shape, two floors building with hipped roof and with basement	$205.46\ m^2$	$234.17\ m^2$	13%
4	residential building of ordinary architectural form; two floors building with usable attic and with hipped roof	$139.60\ m^2$	$147.98\ m^2$	6%
5	residential building of complex architectural shape; two floors building with hipped roof	$171.34\ m^2$	$186.76\ m^2$	9%
6	residential building of ordinary architectural shape; two floors building with gable roof	$169.10\ m^2$	$184.32\ m^2$	9%
7	residential building of complex architectural shape; three floors with usable attic and with hipped roof	$234.90\ m^2$	$263.09\ m^2$	12%
8	residential building of ordinary architectural shape; one floor building with hipped roof	$152.72\ m^2$	$164.94\ m^2$	8%
9	residential building of complex architectural shape; three floors building with usable attic and with double hipped roof and with basement	$197.45\ m^2$	$231.02\ m^2$	17 %

satisfactory differences between estimated and actual UFA. The greatest differences between the area within the obtained homogenous group equalled from 6 % to 17 %. The group of buildings with the most complex architectural shape had the least accuracy, even though it was much more precise than UFA estimated according to the current methods. The less complex the architectural shape, the higher the accuracy of BUFA estimation according to the proposed algorithm. The average BUFA difference value in comparison to actual UFA equalled 9.7 % (worst cases in 9 homogenous groups of properties).

Property is one of the principal anthropogenic components of urban area thus became a subject of thorough multidisciplinary analysis in the field of data requiring spatial information systems. Due to the lack of some of the most important information about usable floor area of residential buildings in public registers, there is a high probability of making inappropriate or not entirely justified decisions for fiscal, investment, urban area analysis. Having that kind of automatic solution enables rapid (and apparently more satisfying) BUFA estimation in comparison with current methods (e.g. presented in Table 3). Moreover, it fills in the gap in identified limitations (Table 4).

The presented limitations in Table 4 are the most common obstacles in calculating or verifying the UFA for residential buildings. The first limitation is related to controversy with respect to capturing and collecting geometric data of the building and ambiguity of the terminology (e.g. overhang, vestibule, veranda). Even though the data collected in the cadastre seems easy to interpret, in reality it causes problems in interpretation without a field inspection of the property. In complex architectural solids of residential houses, what seems to be build-up area in reality can turn out to be an overhang or vestibule. Including those elements in BUFA can lead to gross error occurrence. The algorithm elaborated by the authors decreases problems in using LiDAR observations (substitute field inspection) and machine learning technology (semantic recognition of the building components). The proposed algorithm allows the cadastral data to be verified, thereby allowing data error elimination and misinterpretation of the aforementioned terminology. A quite common situation is the presence of a usable attic in a building which, according to the cadastre, has only one storey. This difference can be caused either by a data error in cadastre or adaptation without a legally required building permit.

Another barrier is connected with updateness (reliability) of the data contained in the property cadastre (or other public registers). This is crucial and one of most important issues related to the area calculation or verification. The particular information is very often either non-existent, false or imprecise. The proposed algorithm is based on LiDAR data of high spatial and temporary resolutions and real actual images which decrease this problem effectively.

The other problem is related to the impossibility of including rooms of different heights in the calculation process. This problem is solved by the proposed approaches using image context recognition (computer vision technology) which enables labelling the particular building elements. The recognition of the windows and doors (involving machine learning technology) enables identification of the storeys directly from the building facade images. This is possible thanks to projective transformation for obtaining metric information about facade objects. The size and location of these objects enabled storey height determination. An additional advantage of the proposed algorithm is its scalability though flexibility related to metric information about the object.

The last issue related to polysemy of the term of usable floor area has still not been solved. This problem remains outside the scope of the following proposal since it is strictly connected with the legal side of it. In the authors' opinion, it can be solved either by legal acts or directives imposing strict rules concerning its interpretation. Further research (connected with further modification of the algorithm) concerning this problem assumes determination of BUFA using different methods. The recipients will, therefore, be able to choose the particular method of BUFA determination depending on the purpose.

Further research will focus on development of the methodology to

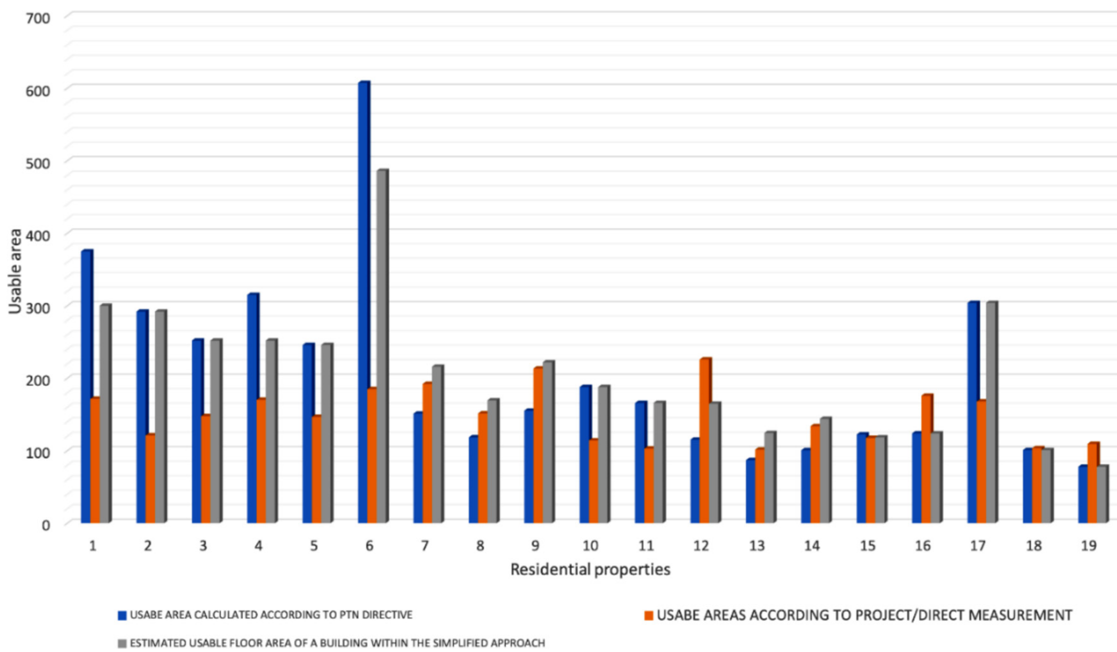


Fig. 14. Comparison of BUFA calculated according to current state of art and direct measure/project.
Source: own elaboration.

Table 4
Comparison of BUFA and the proposed algorithm.
Source: own elaboration.

	Existing concept	Proposed concept
controversy with respect to capturing, collecting geometric data of the building and ambiguity of the terminology (etc. overhang, vestibule, veranda)	–	+
updateness (reliability) of the data contained in the property cadaster	–	+
impossibility to include rooms of different heights in the calculation process	–	+
polysemy of the term of usable floor area	–	–

-Unfilled.
+Filled.

decrease its limitations in:

- calculation of the BUFA on the basis of sections - that disables precise calculation of UFA. This limitation is a very complex issue to solve due to the fact of no direct access to building interior area data. A general consequence of remote solution application is indirect assessment of phenomena with internal structure;
- assumptions based on the roof surface approximated by planes figure – that disables consideration of surfaces with a non-zero curvature. The further development assumes applying different/alternative method (then M-split) to obtained geometric specificity of the roofs;
- BUFA calculation according to certain interpretation (including every particular room to the calculation usable floor area) – this cause problem with interpretation of BUFA for particular purposes and related to them different legal acts/norm/standards. The further development of the algorithm assumes calculation of BUFA with consideration of particular rooms function (e.g. including or omitting the usable area of garages/staircases/basements etc.);
- facades information collection limited to close range photogrammetry images - this causes problem with accessibility to facade view (from every side) that is necessary for identification of number and height of floors based on windows and doors location. This can be very useful for assessment of building technical condition as well. Due to this fact, the further development assumes, using different source of information then just images from street view or own images, using UAV technology or images obtained during the raid targeted (LiDAR).

However, the decrease of limitations presented above does not have to improve the accuracy/effectiveness of the BUFA calculation. These are some constraints in the proposed method, observed during detailed analyses that must be subjected to further tests. Reduction of the presented restrictions may increase precision in exchange for the need for a greater number of information sources analyse, increase of time analyses and difficulties in interpretation. It must be underlined that the use of solutions presented by the authors gave satisfying solutions. Elimination of indicated restrictions may constitute an additional component of the procedure which, in special cases (objects of complex architectural shape) may possibly give better results.

Finally, it must be underlined, that the methodology as a way of data collection can be especially useful in countries of limited possibilities of UFA/BUFA data acquisition/collection. The proposed methodology was elaborated for residential houses needs and any attempt of widening its' scope of application for other residential units needs detailed reconsideration of the assumed solutions.

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CRediT authorship contribution statement

Artur Janowski: Conceptualization, Methodology, Software, Data curation. **Małgorzata Renigier-Biłozor:** Conceptualization, Methodology, Supervision, Formal analysis. **Marek Walacik:** Conceptualization, Validation, Formal analysis. **Aneta Chmielewska:** Validation, Visualization, Writing - original draft.

Declaration of Competing Interest

None.

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