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A 3D optical deformation measurement system supported by knowledge-based and learning techniques

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Abstract. High accuracy 3D representation and monitoring of objects is receiving increasing interest both in science and industrial applications. Up to now tasks like monitoring of building displacements or deformations were solved by means of artificial targets on the objects of interest, although mature optical 3D measurement and laser scanning techniques are available. Such systems can perform their measurements even without targeting. This paper presents a new optical 3D measurement system, based on the fusion between a geodetic image sensor and a laser scanner. The main goal of its development was the automation of the whole measurement process, including the tasks of point identification and measurement, deformation analysis, and interpretation. This was only possible by means of new methods and techniques originally developed in the area of Artificial Intelligence; both point detection and deformation analysis are supported by decision systems that use such techniques. The resulting complex multi-sensor system is able to measure and analyse the deformation of objects, as shown in experiments. In this article we focus on specific key components and novel techniques that have been developed, and briefly report on the current stage of the whole system.

Keywords. Image-based measurement system, sensor fusion, deformation analysis, image-assisted total station, knowledge-based system, learning.

1. Introduction

The increasing number of objects located in highly populated areas that are involved in deformation processes has extended the demand for rapidly working and easily usable deformation measurement systems. Deformation measurement enables the early detection of damage, infrastructure failure or potential hazard due to deformations to enable appropriate reaction in time. The possible causes for such deformations are manifold. To name a few, changes of ground water level, tidal phenomena, tectonic events, or human underground construction can be the reason for deformation of buildings, bridges, dams, tunnels and railway tracks.

A great variety of optical 3D measurement techniques like laser scanners, photogrammetric systems, or specific image-based measurement systems are available to fulfil this need.

Most state-of-the-art sensors must be placed on-site (i.e., directly on the region or object that undergoes a deformation) which is often not possible in hazardous terrain. It is therefore necessary to apply remote monitoring methods that can perform their measurements without depending on targets placed on the object. Important representatives are based on laser scanning sensors (Bauer et al. 2005) or terrestrial synthetic aperture radar (McHugh et al. 2006), both leading to multi-temporal images containing distances to the scene in each pixel. These active sensing systems are measuring/determining only one coordinate component of deformations (changes in the viewing direction). Furthermore, the footprint of such sensors is relatively large (in the range of decimetres), such that a precise lateral location of each measurement is not possible. Distance accuracy of these terrestrial systems is typically $\sim$10 mm/50 m (referred to a single point measurement, cf. Luhmann (2008)). However, they provide a dense grid of measurements, covering a large area without major temporal effort.

To close the gap between these low-resolution, medium-accuracy sensors and conventional (cooperative target-based) surveying methods, a straightforward solution is the fusion of image-assisted total stations (IATS) and terrestrial laser scanning techniques (TLS), which provides high-density deformation fields with high accuracy (down to mm range) in all three coordinate directions. Both sensor units (IATS and TLS) can perform their measurements even without targeting.

The disadvantage of such a complex measurement system is the need for a well trained "measurement expert" who must have specific skills and experience to properly operate the system, both for conducting the measurement process and for the interpretation of its results. From initial image/point capturing to deformation analysis, a series of actions and decisions must be taken, which are highly interdependent. Reliable automatic or semi-automatic object monitoring will only be possible if all the knowledge about the measurement system is available and incorporated in a suitable decision system (e.g., a knowledge-based system). Furthermore, a monitoring system consists of some additional parts – e.g., deformation analysis, deformation interpretation, alerting system, etc.

In an interdisciplinary research project[1] a new kind of image-based measurement framework was therefore developed that combines IATS and TLS systems. It comprises a number of sub-systems, covering image processing, 3D point measurements, deformation analysis, and deformation interpretation. They incorporate new techniques that originally come from Artificial Intelligence and essentially support the measurement, analysis and interpretation task. Based on this framework, a prototype measurement system has been developed; for a representative application case the focus was on the monitoring of buildings and especially of façades.

In this article, we present the novel measurement system. To this end, we first review the state-of-the-art of image-based measurement systems. The main part of the article is then devoted to the newly developed measurement system and its major components, emphasizing on object and single point segmentation, deformation analysis, and deformation interpretation. To show the advantages of the new system, we then discuss some examples. Some final remarks conclude the paper.

2. Image-based measurement system

2.1. Sensors

The **basic sensor** for the optical deformation measurement system is an image-assisted total station. This device is based on a tacheometer with a CCD camera in the optical path, where the images of the telescope's visual field are projected onto the camera chip. Mosaic panoramic images can be captured by driving the axes of the targeting system with computer-controlled motors. With appropriate calibration, the images are accurately *geo-referenced* and *geo-oriented*.

The optical set-up is reduced to a two-lens system consisting of a front and a focus lens. Instead of an eyepiece, a CCD sensor is placed in the intermediate focus plane of the objective lens. The image data from the CCD sensor are fed into a computer using a synchronized frame grabber. The variable camera constant and principal point location resulting from the focus mechanism is compensated by a calibration step and precise focusing encoders. Additionally, the system is equipped with a wide-angle (WA) camera (currently attached at the top of the telescope – in a later development step the integration of this camera into the optical path is envisaged). Also the integration of a scanning device (co-axial) will be possible and realised in the near future. The main problem of such an implementation is the calibration of the

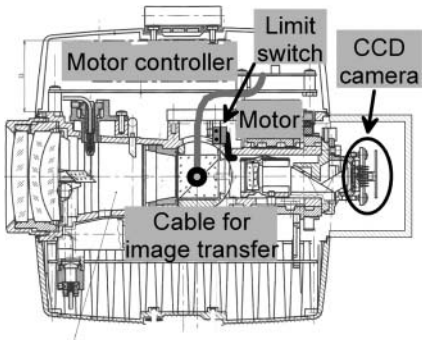


Figure 1: Cross section of the telescope – taken from Walser (2003).

sensors. An optical set-up and the necessary calibration functions for such a system (see Figure 1) were developed by Walser (2003).

In the last years, research activities in the area of image-based measurement systems have been increased. *Leica Geosystems* developed a prototype of an image-assisted total station aiming at a hybrid or semi-automatic approach to combine the strength of the traditional user-driven surveying mode with the benefits of modern data processing (see Walser 2003, Walser and Braunecker 2003). Further work in this area has been done by *Topcon* and *Trimble* (Topcon 2007, Trimble 2007), by the *Technische Universität München* (Wasmeier 2003), by *Ruhr Universität Bochum* (Scherer 2003, 2004), and by the *Vienna University of Technology* (Fabiankowitsch 1990, Roic 1996, Mischke 1998, Reiterer 2004).

The **second sensor** incorporated into our image-based measurement framework is a laser scanning device (TLS). There are quite a few systems on the market with an operating range between near-range (up to 10 m) and 300 m, among others. Laser scanners are well known; for background and detail, see e.g. Cyra (2008), Mensi (2008), Zoller and Fröhlich (2008), and Riegl (2008).

The **integration of IATS and TLS** has a number of advantages. Most notable and important is the possibility to fuse two devices of different accuracy classes, measurement speed, measurement density and point detection concept into a powerful system which combines the highly accurate single or sparse point clouds measurements by an IATS system with the robust and dense point clouds obtained by a TLS. The point-oriented method of the image assisted sensor is suited to capture structured regions (e.g., edges and corners) of an object with high accuracy while the area-oriented method of the laser scanner is suited to survey the unstructured regions (e.g., planes).

Due to the nature of both sensor types, sensor fusion can take place purely based on their ability to rely

1 Project title: *Multi-Sensor Deformation Measurement System Supported by Knowledge-Based and Cognitive Vision Techniques.* The project is a cooperation between the Vienna University of Technology (lead management) and Joanneum Research Graz.

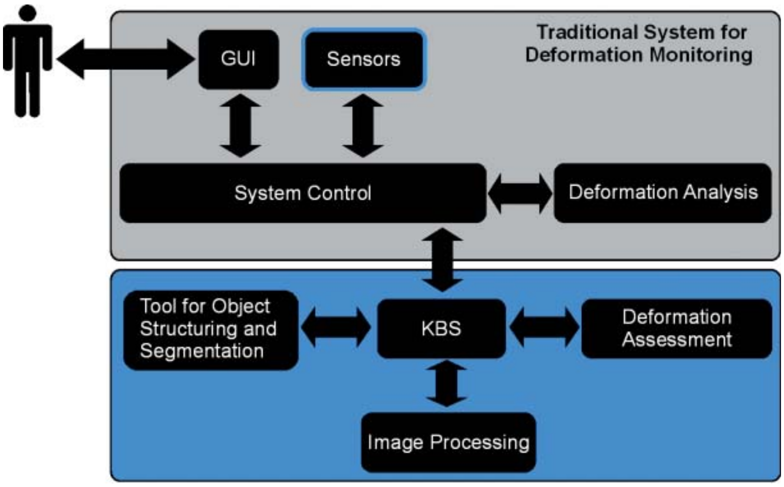


Figure 2: Simplified architecture of the developed system. Upper Box: Conventional part, lower box: New part.

on a geodetic network: Arbitrarily placed reference points in the scene (e.g., reflective prisms, spheres or co-operative targets) can be measured by both sensors to establish a robust 3D co-registration. Furthermore, especially in large regions with unknown deformation distribution a laser scanner system can provide key information for quick decisions (e.g., where monitoring makes sense). On the basis of a multi epoch laser scan (e.g., by scanning a region again after some time interval) a simple comparison of laser distance images helps for determining candidate deformation regions. A combination of these sensors is therefore a promising solution for most types of deformation measurement.

2.2. *Basic measurement concept*

Several research activities (Roic 1996, Reiterer 2004) have shown that the usage of image-based multi-sensor systems is rather complicated. An improvement of the handling can be achieved by equipping the measurement processes with a **decision support system**. A wide range of methods exists in the literature for implementing decision support systems, such as knowledge-based systems, artificial neural networks, or genetic algorithms (Turban et al. 2004). For our framework, we adopted a knowledge-based approach. The advantages of knowledge-based systems in comparison with other concepts are manifold: The knowledge about the problem domain is separated from general problem-solving knowledge, which makes it easier for the knowledge engineer to manipulate this knowledge; not only hard knowledge can be represented, but also fuzzy knowledge (which is useful and potentially very profitable); the expert knowledge, which very often has the form of rules, can be captured in this form without the need for converting it into other (little accessible) representation forms.

We emphasize that a complex multi-sensor approach is complicated to handle, and requires a new form of **system concept** that integrates the decision-support. In our approach, the system thus consists of the following components:

- the sensors,
- a subsystem for controlling all units (system control),
- a subsystem for deformation analysis,
- a subsystem for deformation assessment,
- a knowledge-based decision system (KBS),
- a subsystem for object segmentation,
- a tool for image processing, and
- a graphical user interface (GUI).

The system architecture is based on two central components, which are the system control and the KBS; all components are controlled by them. The modular concept leads to a system that is easy to maintain (each component can be modified separately, and programming bugs can be localized more precisely). A simplified view of the system architecture is shown in Figure 2. The upper part of the figure (grey box) shows the traditional part of the system, complemented by the new integration and fusion of IATS and TLS (indicated by blue box margin). The lower part of the figure (blue box) shows the newly developed system components, including the knowledge-based decision-support system. As all communication between the two system parts is between the sensor system control unit and the KBS only, the connection is simple and communication errors can be minimized.

The KBS consists of several **KBS-subsystems**, which support the measurement expert on several levels of decision making. The subsystems are designed for a specific task, such as the selection of algorithms during image capturing and point detection, for object structuring and segmentation, or for deformation analysis support. A very important feature of all KBS-subsystems is the possibility for the user to intervene and overrule decisions.

2.3. *Measurement procedure*

One of the main goals of our development was the automation of major parts of the measurement pro-

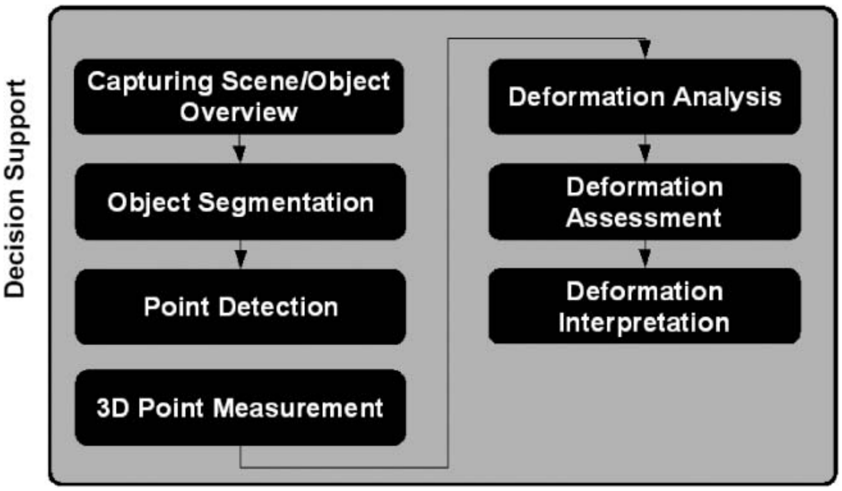


Figure 3: Measurement procedure.

cedure, taking profit of the multi-sensor approach. Figure 3 gives an overview of the whole procedure, whose steps are briefly described as follows.

The measurement process starts with **capturing a scene overview**. Both sensors can execute this task – an overview image can be produced by a LS-intensity image or by an IATS images. The main idea for capturing an overview is to have a basis for global decision-making. By means of this data an analysis process is executed that outputs a formal "object/ scene description" (see Section 3). This description can be used for different decisions; we use it for **structuring and segmenting the object.**

The main goal of this structuring process is to enable the system to use a similar way of point/region selection as a measurement expert. Human experts usually select object points in consideration of the topology. In case of a façade, they select points around windows and doors, as well as around other striking object features. This is well-founded by the natural human attitude to transform a complex form into a simple representation using clear textured features (in this context, the term "visual intelligence" is appropriate).

The final result of the structuring process is the definition of *Regions of Interest* (**ROIs**). A ROI is, roughly speaking, the boundary of an interesting area. The most important question is how such a region can be described and depicted. For a deformation measurement system as described here, the ROIs have to satisfy two conditions: (1) they have to characterise the whole object deformation, and (2) they have to include well-structured object parts that allow automated point detection. On the basis of these ROIs **3D object points** can be **detected**. For point detection by means of the IATS, images are captured by the internal camera and image point detection algorithms are applied. More details about point detection can be found in Section 4.

One precondition for **deformation analysis** is the existence of more than one **measurement epoch**. Provided that such measurements are available, the developed system can process a classical deformation analysis followed by a deformation classification process (**deformation assessment**) (see Section 5). As a last step **deformation** can be **interpreted** automatically.

Starting from object structuring, all processing steps are aided by suitable decision-making support (either fully- or semi-automated). In the following sections, we will describe these steps in more detail.

3. Object segmentation

As mentioned above, object segmentation is needed for the subsequent ROI and point detection. Generally, object structure is a very useful feature for several processing steps. In most cases identifying predefined feature elements can help generate such a structure. Therefore the most important step for object structuring is to *formulate a set of feature elements* that represent the object in an adequate form. Our system design is focused, in this prototype stage, on monitoring of building façades, which are mainly represented by windows and doors. Therefore we can use these feature elements for structuring our objects.

For a robust object segmentation procedure it is recommended to use all available measurements. Therefore this subsystem is based both on IATS and TLS data. This approach results in three different object segmentation procedures, which perform object structuring

- by Histogram Median Filtering (Section 3.1),
- by learning (Section 3.2), and
- on the basis of captured TLS point clouds (Section 3.3).

Different from that last method, the first two methods operate on images. While these procedures are currently geared towards facades, they will in future stages be extended to and/or complemented with segmentation procedures for other object types such as rock falls. Furthermore, the choice of a suitable method depending on object and scene conditions us-

(a) (b) (c)

Figure 4: Example for different type of façades: (a) classical, (b) modern, (c) ordinary.

ing a knowledge-based approach is envisaged, similar as for selecting image processing methods on the basis of image analysis in Reiterer (2004). To this end, the realization of a more comprehensive knowledge-based object information system for supporting the structuring process is planned. In the following the three complementary approaches to object segmentation are introduced.

3.1. *Object structuring by Histogram Median Filtering (HFM)*

The basic idea of the first method is to use the vertical and horizontal histogram of the image to separate irrelevant from important structure. The procedure works at several different orientations and scales. The performance has been tested by an evaluation using the Vienna (FdbV 2008) and Zurich (ZuBuD 2007) database sets of façade images, showing that window coordinates can be reliably detected.

The method works in four steps. In the first step, the façade in the image is classified into one of three types: classical, modern, or ordinary; Figure 4 shows some examples for these types. After that, appropriate image pre-processing algorithms are used. In the third step, thresholding techniques are applied, and in the fourth and final step, the image is segmented using Histogram Median Filtering (HMF). The *probability distribution function* has been used to differentiate between the three types of façades: modern façades have an accumulation of very low values; classical façades have an accumulation of high values due to the texture; all other façades are classified as ordinary. In the current prototype, classification is performed manually, while for later versions the integration of automated classification developed in Reiterer (2004) is planned.

For noise discarding, the image has to be preprocessed, where the choice of pre-processing algorithms depends on the type of façade. For example, ordinary buildings need pre-processing steps such as histogram normalization and equalization to be applied, whereas classical buildings usually need contrast stretching. Modern buildings require unsharp masking, because the windows are too bright.

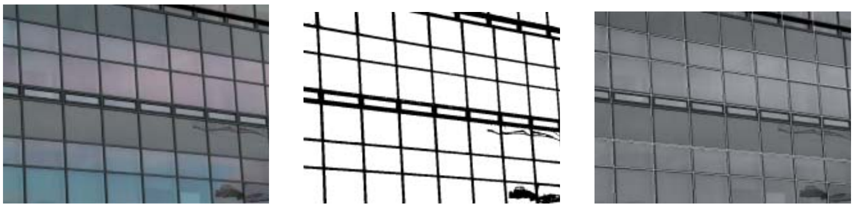
In order to separate an object from the background (in this case a window/door from the façade), an appropriate threshold needs to be chosen to exploit a bimodal histogram distribution: Windows and doors in façades follow a particular pattern, and they have similar pixel values (due to their similarity). The distributions are broad and may overlap. Possible problems include shadows because they are dark and may be classified as an object. After thresholding, which is tuned for these specific objects, the user is supported by a binary image, containing the information on the objects present in the building.

The next step is to calculate horizontal and vertical histograms Hh and Hv. Windows and doors are usually aligned in rows and columns, i.e., they form a specific pattern. The distribution of the two histograms will have an accumulation of high values when processing an area containing windows. Therefore, after the calculation of the two histograms, the values that are greater than the medians will hold the position of the window/door along the horizontal and vertical axes. Windows parallel to other angles than vertical and horizontal are handled by histograms at predominant angles, which are determined by line fitting. The result of our procedure for an example façade (modern type) is shown in Figure 5. More details and an experimental evaluation can be found in Miljanovic et al. (2008).

3.2. *Object structuring by learning*

For the second method we introduce a learning classifier system that provides single window detection and localization, and, at the same time, a window region of interest (WROI) operator that is a basis for further processing.

The feature detection system (Figure 6) is outlined in a pipeline for training and testing related processing components. Once a cascaded classifier has been learned applying an Adaboost method (Freund and Schapire 1996), it is directly applied to the preprocessed image data. The output of the execution module is a list of coordinates of the bounding boxes of hypothesized window related sub-images with respect to the original image frame.



(a) (b) (c)

Figure 5: Image sequence (modern façade) processed by the HMF operator: (a) original image captured by the WA-camera; (b) after thresholding; (c) segmented image (overlaid to the original image).

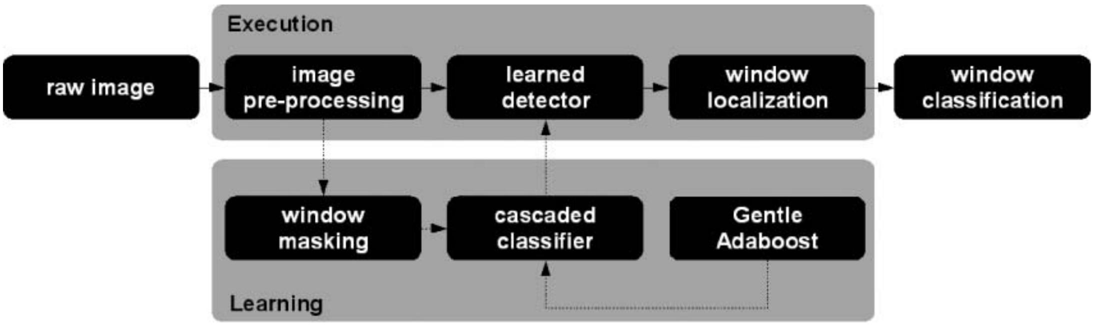
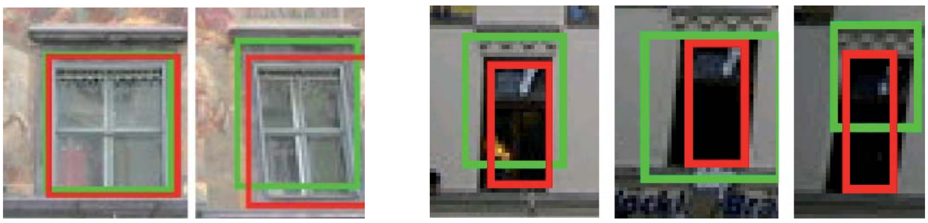


Figure 6: Schematic outline of the window detection system. Dashed lines refer to the learning system.



(a) (b)

Figure 7: The evaluation of the window detector was based on the quantification of the overlap between the actual window (ground truth, red bounding box) and the localization that is hypothesized by the window detector (green bounding box). Sample cases of *positive true* evaluation for (a) single window (SW) based and (b) windows region of interest (WROI) based detection.

The presented method for window detection includes appropriate early image processing, and provides a multi-scale Haar wavelet representation (Aboufadel and Schlicker 2005) for the determination of image tiles, which is then fed into a cascaded classifier for the task of window detection. The classifier is learned from a Gentle Adaboost driven cascaded decision tree (Ali et al. 2007) on masked information from training imagery. It is tested on window – based ground truth information, which is, together with the original building image databases, publicly available (TSG-20 2007, TSG-60 2007, ZuBuD 2007).

The experimental results on standard benchmarking image databases fulfil the requirement that regularly distributed windows should be detected to perform an adequate ROI definition (see above). However, it is noted that the system provides better results on more textured images/objects, such as classical buildings. An example for the detection of windows can be found in Figure 7.

3.3. *Object structuring from 3D laser scanner data*

For the third method we have developed a robust system for structuring using popular descriptive statistics and image-based methods, making use of 3D information from a laser scanner (Figure 8). The laser scanner (Riegl 2008) generates 3D point clouds containing intensity and distance information in a spherical co-ordinate system, with optional additional RGB texture. The applied descriptive statistical method exploits basic local features such as mean, variance, and standard deviation of the distance measurement data. We evaluate the distance information by calculating a local difference of adjacent distances in the angular co-ordinate system of the scanner. An adaptive threshold on the local absolute difference of these distances is determined to identify and select only the data, which represents a ROI, being a candidate for a single region. The identified points above the determined threshold value can be aggregated to ROIs: The laser distance infor-

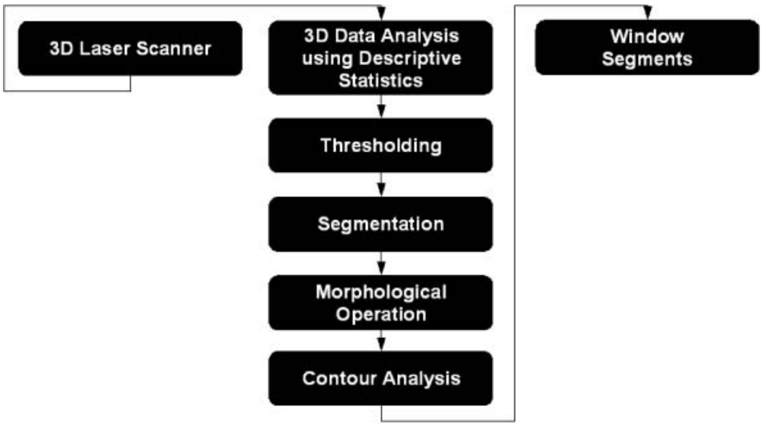


Figure 8: Pipeline for window detection from 3D laser scanner data.

(a) (b) (c)

Figure 9: (a) Original image in laser scanner spherical geometry; (b) Candidates for window sub-segments (binary, overlaid on (a)); (c) Window Segments marked with yellow rectangles.

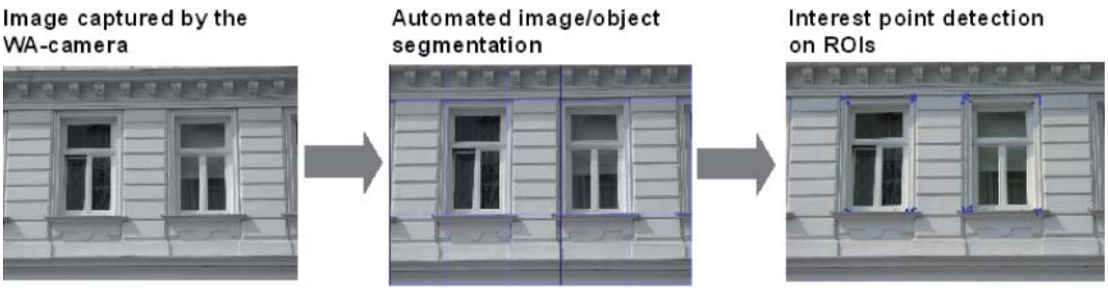


Figure 10: Processing sequence of image point detection: An overview is captured by TLS or by the IATS WA-camera. In a second step image/object segmentation is done. On the basis of this object structure ROIs are defined and IPs detected (in the image IPs are overlaid to the WA-image).

mation shows high variability in windows region, due to specular reflections on window screens on one hand, and screen penetration on the other hand. For segmentation the image is binarized, and morphological operations such as closing using adaptive (i.e. distance-dependent) structural elements are performed. After contour analysis the resulting bounding rectangles are used to retrieve the positions and global shapes of windows in the image.

The output of the execution system is the image with bounding rectangles as shown in Figure 9. First tests have shown that the system provides a sufficient detection rate for the application in a deformation measurement procedure. Nevertheless, this sub-system has to be improved for the application in practice (Ali et al. 2007).

4. Single point detection

Using the detected object structure and the assigned ROIs (see Section 2.2), individual interest points (IPs) need to be detected (see Figure 10). For the task of high precision point detection both sensor units can be used (IATS and TLS). In the following we will focus our description on the point detection by means of the IATS.

The internal camera of the IATS captures images covering the extracted ROIs (the internal camera is

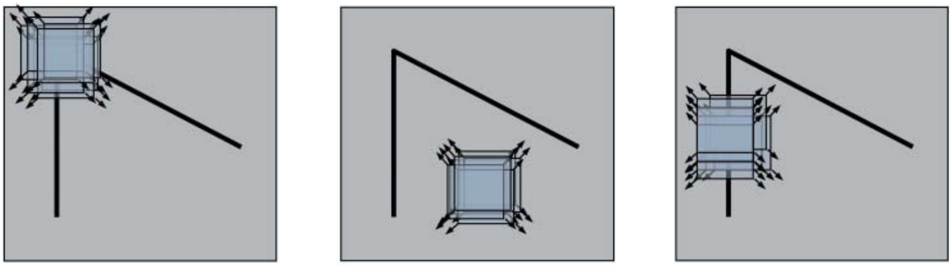


Figure 11: Basic idea of an interest operator (taken from Baltsavias and Papasaika (2007)) – a window is shifted over the image: (a) "flat" region – no grey value changes in all directions; (b) "edge" – no grey value change along the edge direction; (c) "corner" – significant grey value change in all directions.

used instead of the WA-camera due to the larger image scale and in consequence the higher accuracy of image point detection). As a first step image pre-processing can be performed to transfer the image into a form which is better suited for the subsequent automated image point detection (this part is based on knowledge-based decision-making and has already been published – more details can be found in Reiterer (2004)). On such processed images, single interest points (IPs) can be detected by *interest operators* (IOPs). Among the large set of available IOPs (e.g., Förstner 1987, Harris 1988, Moravec 1977) none is suitable for all IP types.

The IOP algorithms implemented in our system can be classified as *intensity-based methods* (see Schmid et al. 2000). These methods build upon a development by Moravec (1977): grey value differences are measured between two image parts – one fixed and the other one shifted in the four directions parallel to the image rows and columns (Figure 11).[2] The size of the shifted part can be fixed individually – typical values are 3–10 pixels. An interest point is detected if the differences of the grey values in the four directions are significant (greater than to an individual fixed threshold). Today there are different improvements and derivatives of the *Moravec* operator. Among the best known are the *Förstner* and the *Harris* operators, which represent two methods implemented into our system. Additionally, we have integrated the *Hierarchical Feature Vector* (HFV) operator based on a dense texture matching approach (Paar and Bauer 1996). The integration of more than one IOP enables a selection on the basis of object characteristics. As in image pre-processing this part has been automated by the integration of a knowledge-based decision system; details can be found in Reiterer (2004).

One advantage of the suggested processing sequence (ROI detection and subsequent point detection) is the restriction of IPs on specific object regions (points are only detected inside the ROIs; see Figure 10).

5. 3D point measurement and fusion

Once the IPs have been detected in single IATS frames, a set of considerations and tools is necessary to obtain a temporal sequence of deformation vectors:

- Sensor orientation for IATS and TLS takes place by signalized points and/or prisms.
- For single-IATS usage, measurement in object space can be performed on the basis of the extracted image points, which is comparable to measurement by a conventional tacheometer (horizontal angle Hz, vertical angle V and distance D). In a subsequent processing step, 3D object coordinates can be calculated which are directly usable for 3D deformation analysis.
- For double IATS acquisition, using the forward intersection principle (Roic 1996) can lead to much higher accuracy and higher distances, since no direct distance measurement from the IATS is necessary. Here, standard stereo matching methods can be used between the two IATS images on the same target point, supported by the TLS structure data usable for pre-registration (e.g., determining the local plane around the current IP to be used to map the first image to the second, thus gaining textural similarity for matching facilitation).
- Multi-temporal measurements require the recognition of each IP of Epoch 0 in each later epoch without loss of accuracy. This is currently supported by a robust matching technique – we are using the HFVM algorithms (Paar and Bauer 1996) in combination with the above mentioned object structuring tools. Matching the points in image space and transforming them into object space enables the measurement of corresponding points in different time epochs.

Besides the detection and measurement part, the final operational system needs a point and data management system. For this purpose, we utilize the functionality of an integrated deformation analysis sys-

2 These "windows" should not be confused with the ROIs.

tem. A big advantage here is that data of different origin (IATS, TLS, etc.) can be stored in a unique format (assuming that the deformation analysis system supports all included sensor systems and all data formats); this is one of the reasons for our use of the GOCA system (GOCA 2008).

6. Deformation analysis and assessment

6.1. Deformation analysis

For monitoring deformations, the object and its surrounding have to be modelled which means dissecting the continuum into discrete points. On the one hand these points should characterize the object, on the other hand their movements represent the object movements and distortions. Modelling the deformation of an object means to observe the characteristic points in certain time intervals by means of a suitable measurement system in order to properly monitor the temporal course of the movements.

To perform a classical **deformation analysis**, several software packages can be used. As mentioned above, we are using the GOCA system, which has the advantage to perform all processing steps in real.

By means of the analysis, process reference point coordinates (initialisation) and object point coordinates (geo-referencing) can be determined by network adjustment. With measurements in different time epochs the investigation of unstable reference points and a deformation analysis (trend estimation, Kalman filtering, Finite-Element-Method (FEM), and, in consequence, alarm management and further prediction) can be performed.

The result of this deformation analysis is a list of points that have significantly moved between the epochs, including the covariance information of their deformation.

An important note is that the standard, procedural method of the deformation analysis aims to process *single points* and their motion. In a classical deformation analysis process, the interpretation of the determined deformation (reasons, effects, etc.) has to be done by an expert. The main idea of the deformation measurement system presented in this paper is to enable the system to automatically help the user/expert to interpret the object motion/deformation.

6.2. Deformation assessment

The process of transforming the data from classical deformation analysis to a form suitable for automated interpretation can be termed as **deformation assessment**. Until this stage of the process, the deformation investigation was done for all points measured on the object's surface. Now the definition of the ROIs earlier in the process comes into operation (see Section 3). A first step is to find a *description of the deformation* of each ROI. This description is based on splitting the determined deformation into its basic motion components by means of an affine transformation. In consideration of the precondition of using compact and solid ROIs, the scaling is not considered in the affine transformation. The method only handles translations along (t_x, t_y, t_z) and rotations (α, β, γ) around the coordinate axes.

To determine the transformation parameters for a ROI, including their standard deviation, all points of the ROI with a significant motion are bundled, and a *Gauss–Helmert* equalization is performed. A precondition for this processing sequence is to have at least three points per ROI (the distribution of these points in the considered region is almost irrelevant; see Lehmann and Reiterer (2007)).

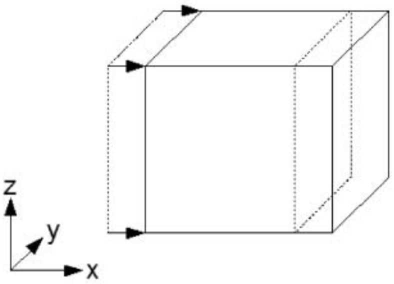
To extract more suitable values for the subsequent processing steps, we use a *fuzzification procedure*. This procedure translates the input values (deformation parameters) into linguistic concepts, which are represented by abstraction ("fuzzy") sets. Fuzzification is done by means of overlapping triangle membership functions. The use of such an abstraction procedure permits us to write rules in terms of easily understood word descriptors, rather than in terms of numerical values.

A simplified description for two prototypical motions of a ROI is shown in Figure 12. The first example shows a translation along the x-axis. The value "1" in the "zero"-row of each column except t_x means that the corresponding variable (α, β, etc.) has no significant value. The value "1" in the medium-row of the t_x-column means that t_x has medium value, which is here then the overall fuzzy-value of the translation. The parameter in the second example (small rotation around the y-axis) can be interpreted in the same way. Currently we are using only fuzzy values of 0 and 1 – in a future step a more detailed fuzzyfication is envisaged.

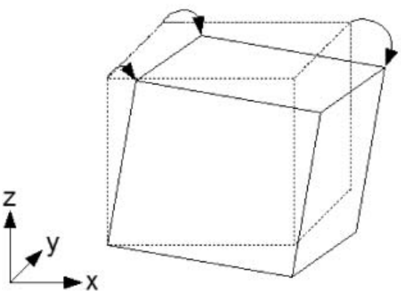
As already mentioned, the system follows a local-to-global information integration strategy. The combination of the results of the ROIs in a later step offers the possibility of detecting changes in both the outer geometry (rigid body motions) and the inner geometry (distortions, bending) of the object.

To draw a conclusion about the deformation of the whole object, a *deformation pattern* has to be formed by grouping the results of the regions. Due to the circumstantial and complex procedure of grouping the ROIs by their specific parameters and/or fuzzy values, we developed a more general description on the basis of *deformation cases*.

A **deformation case** is a unique combination of fuzzy values of the specific motion parameters. By means of well-known, prototypical deformation cases a special *codebook* of deformation characteristics can be implemented. To determine the generalized description, a matching between cases in the database (codebook) and a new (unknown) case can be processed by



fuzzy values	deformation parameters					
	α	β	γ	t_x	t_y	t_z
very huge negative	0	0	0	0	0	0
huge negative	0	0	0	0	0	0
medium negative	0	0	0	0	0	0
small negative	0	0	0	0	0	0
very small negative	0	0	0	0	0	0
zero	1	1	1	0	1	1
very small	0	0	0	0	0	0
small	0	0	0	0	0	0
medium	0	0	0	1	0	0
huge	0	0	0	0	0	0
very huge	0	0	0	0	0	0



fuzzy values	deformation parameters					
	α	β	γ	t_x	t_y	t_z
very huge negative	0	0	0	0	0	0
huge negative	0	0	0	0	0	0
medium negative	0	0	0	0	0	0
small negative	0	0	0	0	0	0
very small negative	0	0	0	0	0	0
zero	1	0	1	1	1	1
very small	0	0	0	0	0	0
small	0	1	0	0	0	0
medium	0	0	0	0	0	0
huge	0	0	0	0	0	0
very huge	0	0	0	0	0	0

Figure 12: Two examples for deformation parameters, their fuzzy values and the corresponding motions.

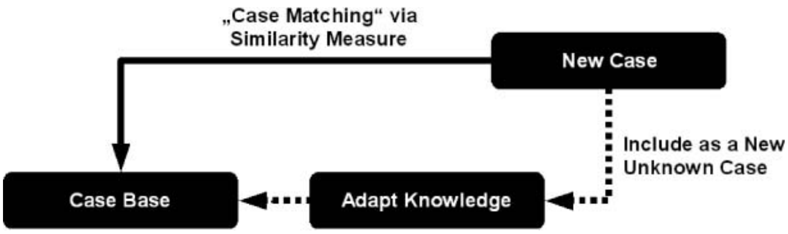


Figure 13: The simplified CBR cycle.

case-based reasoning (CBR). CBR is a methodology from the field of Artificial Intelligence that can use different techniques to solve a problem by resorting to the solution of a similar problem that occurred previously (Watson 1999). An overview of the typical CBR cycle is shown in Figure 13.

The range of useable techniques for CBR is quite large (artificial neuronal networks, genetic algorithms, knowledge-based systems, etc.). In our framework, we use fuzzy logic and knowledge-based system techniques. They are both based on fixed knowledge that is included in a general knowledge base (see Figure 2).

In our application, the cases in the case base are artificial prototypical combinations of fuzzy values of the deformation parameters. Thereby all combinations of the motions (rotations and translations) are included. Now given a new case (in terms of a ROI), the CBR system compares it with the cases in the case base and determines a measure of similarity, the so-called *score*. Applying this to all ROIs, we get a list where every ROI is assigned to one of the prototypical cases. If no matching case is found, the case base can be updated. A realization of this system using the CBR Shell of the University of Edinburgh (AIAI 2007), which is a ready-to-use implementation of a CBR tool, was easy. For performance reasons, however, we developed a plain native system for generating descriptions (hard-coded comparison of the fuzzy values with the prototypical cases), which however does not allows to adjust the case base when the system is in use.

After the generalized description of each ROI in terms of a deformation characteristic is obtained, the descriptions of related ROIs are combined into a **deformation** pattern. On the basis of this deformation pattern, an interpretation of the deformation is made. This part is still in development (concept/study) – we plan to use a knowledge-based approach including knowledge from different origins (e.g. engineering sciences, geology, etc.). A colour-coded representation of such a pattern grouping is shown in Figure 14. ROIs with the same colour represent the same movement and are summarized by a bold line.

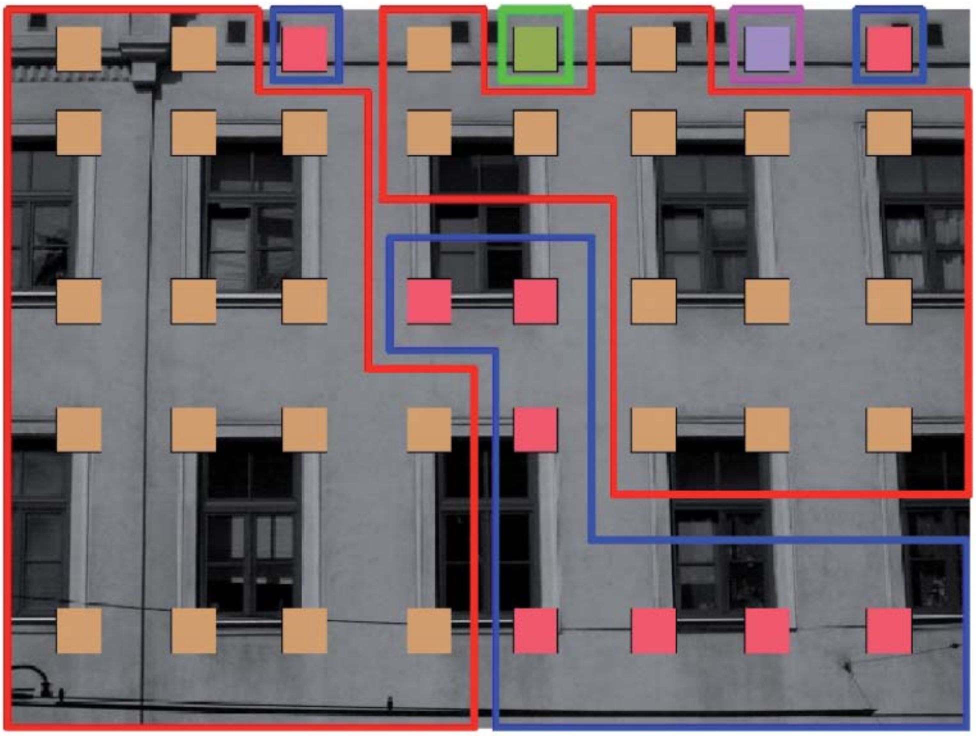


Figure 14: Example of grouping of movement patterns – same movements/deformations are coded by the same colour (red – pattern 1, blue – pattern 2, etc.).

As mentioned before, one main goal of our research work is to extend the classical deformation analysis, which aims at single points, to a more global working, point-set oriented procedure. The results of this process can be used as basis for automated deformation interpretation. The main task of the interpretation is to generate assumptions and hypotheses, which have to be stated and tested by new measurement data from subsystems or by human interaction.

In order to formulate a reliable interpretation, an adequate model of the structure is required. In a first development stage, the suggestive integration of a FEM as the best fitting model was considered. This approach, however, is too complex for an operational procedure (the underlying physical models are not sufficiently detailed or are affected by missing data). Therefore, a simpler method was developed to describe the structure appropriately. Some of the instances of the corresponding model will include material attributes (of the building), description of the soil underneath the construction site, etc. These instances represent additional information that could be inserted manually to the system by the user, preferably by an experienced engineer (the model could be loosely based on the FEM. The collected information can be used by the user or by a knowledge-based diagnostic tool for the interpretation of the deformation.

7. Conclusions and future work

We presented the framework of a novel optical 3D multi-sensor system towards automated deformation measurement, which has several innovative features. A core sensor component of this system is an IATS, which is extended by a terrestrial laser scanning device; the integration of these sensors has several advantages. Object segmentation and detection of interest points and regions of interest is carried out (semi)-automatically, using knowledge-based techniques, for which knowledge of different provenance (from geodetic and civil engineering experts, but also on image processing and structural engineering) has been compiled in order to provide decision support. The detected points and regions of interest are the basis for identifying deformation primitives; beyond traditional pointwise deformation analysis, sets of points are considered and by means of Artificial Intelligence techniques classified into a set of deformation cases. The detected deformation cases are input, together with other data, to the deformation interpretation, which provides an assessment using integrated expert knowledge.

Based on this framework, a prototype measurement system has been developed, whose current status is summarized in Table 1. While the prototype verifies the whole workflow from image capturing to the output of the deformation assessment, not all modules are fully integrated yet, and deeper assessment of the detected deformations that exploits richer knowledge remains to be developed.

The mid-term vision is the development of a fully integrated and highly automated on-line measurement system that is supported by image-based measure-

Table 1: Status of optical deformation measurement system.

Module	Functionality	Integration Status	Implemented Knowledge Base for Decision Support
Sensor Control & Measurement	IATS acquires 3D data points TLS orientation & data acquisition IATS stereo forward intersection	Integrated Standalone Concept	none
Sensor Fusion	TLS used for decision on IATS Measurement	Standalone	none
Object Segmentation and ROI Detection	Select regions of interest (ROIs) for the subsequent selection of object points	Integrated	Geodetic Image Processing
Point Detection/Selection	Interest points autonomously detected/selected	Integrated	Image Processing
Points/Regions Database	3D Points & Regions maintained and sought again in later epochs	Integrated	none
Deformation Analysis/ Assessment (CBR)	Analyse point clouds of different measurement epochs and detect significant movements	Study	Geodetic Civil Engineering Structural Engineering
Deformation Interpretation	Interpret the detected movements by means of integrated expert knowledge	Concept/Study	Object Type Deformation Assessment

ment and laser scanning techniques. The integration of further sensors (GNSS, PMD, etc.) will be a challenging task as is in the long term to obtain interpretation results for deformations at a deep level of expertise, which may also offer possible explanations. While the degree of automation can be very high in decision-making, human intervention remains an important element of the workflow even if the number of user decisions can be reduced to a minimum. A short-term target is to limit the need for human interaction to high-level decisions, thus avoiding manual observations for single point measurement on a total station ocular.

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