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METHOD OF IMPROVING INCOMPLETE SPATIAL-TEMPORAL DATA IN INLAND NAVIGATION, ON THE BASIS OF INDUSTRIAL CAMERA IMAGES – WEST ODER RIVER CASE STUDY

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Main aim of the paper is to use a single non-metric camera to support the determination of the position of. Authors propose to use the existing infrastructure of CCTV cameras mounted on bridges and wharves to determine the position of inland waterway vessels. Image from cameras giving the pixel coordinates of moving object is transformed to the geodetic data domain using a modified projective transformation method. Novel approach is to use of Sequential Projection Transformation (SPT) which additionally uses virtual reference points. The transformation coefficients calculated using the virtual points are used to determine the position of the vessels and are also simultaneously used to calibrate the industrial camera. The method has been verified under real conditions, and the results obtained are average 30% more accurate compared to the traditionally used projective transformation using a small number of real points.

Keywords: freight transport, geodesy, image processing, spatial data, inland navigation, industrial camera

1. Introduction

The paper presents the Sequential Projection Transformation (SPT) method of improving the determination of the vessel position obtained by non-metric stationary industrial cameras working already as video monitoring stations in inland waterway environment. For this purpose, it was necessary to perform the survey of fixed objects (wharf, bridges) and use them as reference points for the transformed image. In addition, the virtual points (marks installed and surveyed on floating boat) were used for transformation. It enabled to achieve accuracy within the limits of GNSS receivers mounted currently on inland vessels over a larger area than before. The increasing number of inland vessels both cargo and recreational on European inland waterways, is a reason to explore a new, alternative means to minimize the associated risk to vessel traffic and to provide reliable tools for navigation monitoring. In aspect of collision, the most vulnerable places are primarily the intersections of waterways with roads and rail infrastructure, in the form of bridges and viaducts. A collision between a ship and a piece of road infrastructure can have wide-ranging consequences for both waterborne and land-based traffic.

An analysis of the intensity of ship traffic per year, within the inland waterways of large cities in Poland, using specifically the example of the city of Szczecin, shows that in the area of bridges where regular shipping takes place the large accumulation of vessels was observed (figure 1). It is worth noting The Commission Regulation (EC) (European Commisin, 2007) based on Directive of the European Parliament (Parliament *et al.*, 2005) and the recommendations of the European Commission (Europe and COMMITTEE, 2005) suggest the use of stationary cameras for monitoring of inland waterways. Unfortunately, its role in the river transport comes down to passive observation of the navigational situation.

Figure 1. Spatio-temporal data of passing vessels density near the City of Szczecin agglomeration.
Source: www.marinetraffic.com. Access: May, 2021

Taking into account the fact that the coverage of river areas by CCTV cameras is increasing, we came up with solution to utilise them as an independent from vessel, source of vessels' position. Such a tool could be used for detection and tracking of inland vessels what fulfils the need for an autonomous system serves as alternative to Automatic Identification System (AIS). The extensive research withing the area of image processing has been published so far. In the 1980s, the increase in computing power of computers contributed to an ever wider use of machine vision methods for the automatic analysis of video images in road transport. One of the first publications of this type was a study by the authors (Dickinson and Waterfall, 1984; M R Wigan and Cullinan, 1984; M. R. Wigan and Cullinan, 1984), who investigated the robustness of image analysis algorithms to changing lighting conditions and dynamic changes of moving objects. The growth of this field of science, was associated with the simultaneous development of mathematical methods such as contextual, point and morphological transformations. The researchers (Matthies, Kanade and Szeliski, 1989; Ali and Dagless, 1992) have improved the efficiency of image processing algorithms, especially the quantitative and qualitative analysis of images, allowing real-time interpretation of the results.

The last two decades have brought development and implementation of image recognition methods using classifiers (Kandil and Atwan, 2012; Anitha and Deepa, 2014), databases of selected object features (Li, Liu and School, 2013; Pamula, 2014), and neural networks (Maddalena and Petrosino, 2008; Zhou *et al.*, 2021). It is not uncommon for a combination of many of these methods to be used in augmented reality systems available directly to drivers and road transport management systems. Rarely, the mentioned methods has been adopted into waterway transport. So far in industry, the focus has been mainly put to the detection of an object and its tracking or recognition of the type of inland vessel passing through the milage point.

In order to make images from industrial cameras useful for automatic analysis of navigation situation, image processing algorithms should be used for detection of moving objects and their tracking in the field of view of the camera. Projection transformation of digital image plane into the points of geographic coordinate system should be performed. Both techniques are widely used separately, however they are rarely used simultaneously due to the complexity and limitations of the output material from a single, non-metric, stationary industrial camera. Non-metric single industrial cameras find its application in inland navigation as a single and fixed positioned camera. These cameras are hardly utilised for vessels' position determination, even though they are mounted in places of importance for the safety of navigation. This is usually due to the fact the cameras are perpendicular to the water surface, which

introduces significant distortions of perspective. The usage of a single, stationary, non-metric camera in a waterborne transport causes issues not encountered in road transport. First of all, the dimensions of potential objects is in most of the cases much larger, ranging from small units of about 2m to quite common pushed sets, reaching up to 120m in length. An additional problem to be solved in water transport is the variability of the light background, which is the greater issue comparing to road transport. Reflections generated by the water surface require the use of modified methods of image processing. The papers (Frost and Tapamo, 2013; Moreira *et al.*, 2014; Kujawski, 2015) present the differences of individual algorithms suitable for vessel shape detection estimation such as Kalman filter, Mean-Shift, SURF, contour detection, mixture of Gaussian, optical flow and their robustness to changing lighting conditions and the large variety of vessels appearing in the field of view of the camera. It has been shown that not all algorithms are robust to scale change of objects and such scale change is encountered when tracking vessels over long distances.

Other image analysis methods involve object feature databases to detect predicted feature sets such as shape, colour, size and also use of neural networks for machine learning (Wawrzyniak and Stateczny, 2018; Nie, Yang and Liu, 2019; Wawrzyniak, Hyla and Popik, 2019; Cao *et al.*, 2020; Wang, Wang and Er, 2020). The advantage of the recent ones is the possibility of elimination the messy effects associated with the light conditions that have a negative impact on the effectiveness of object detection in a water environment. In river and deep-sea navigation is supported by a broad range of navigation equipment. However, unlike sea navigation, the river fleet consists of small boats and yachts to long pushed sets (pusher plus barges). What are more the regulations and recommendations are not the same for all traffic participants. The requirements to the navigational aids are set depending on the type and dimensions of the units. One of the elements of harmonized river information services is the AIS (Automatic Identification System), which is a radio system for the exchange of static and dynamic data between ships and coastal stations.

The accuracy of the DGNSS (Differential Global Navigation Satellite System) used as a source of position in AIS was described by (Specht, Specht and Dąbrowski, 2019). Although the local availability of the DGNSS system on the Lower Oder River was determined by (Banachowicz *et al.*, 2008; Wisniewski, Bruniecki and Moszynski, 2013) the new research is required after new generation receivers compatible with Globalnaya Navigacionaya Sputnikovaya Sistema (GLONAS) and European Global Navigation Satellite System (GALILEO) signal were introduced much wider. In addition to not perfect technical parameters of the GNSS in area, there are other elements that reduce the precision, reliability and availability of the information transmitted by AIS devices. These are elements of road and rail infrastructure, which construction and location adversely affect the transmission and reception signal of AIS. Loss of navigational information also affects the centre of the waterway where the gaps in messages or erroneous data occur. The cumulative effect of all types of mentioned disturbances are shown in Figure 2. In the general the lack of continuity of AIS messages is observed. The enlarged view presents erroneous positioning data.

Figure 2. Spatio-temporal data interference in centre of waterway and near the navigational obstacles (enlarged view)

To be able to apply not metric camera as positioning source the method of transforming image data expressed in pixels into geographic coordinates by means of image projective transformations with additional use of so-called virtual points was proposed. As a result of research, even though the image plane is geometrically unfavourable in relation to the water surface, and the industrial camera can be used to position vessels for inland navigation purposes. The proposed approach improves the positioning accuracy of floating objects over the traditional application of projective transformation using real points. The approach solves the issue of using the set of single non-metric cameras, mounted on bridges of the western Oder River, for positioning rather than just monitoring. The proposed method can also be applied to the transformation when there is only water in the camera image and no fixed reference points.

2. Materials and Methods

Coordinate transformations in orthogonal reference systems are generally based on transformations by similarity, called also Helmert or conformal transformation (Baetslé, 1966; Späth, 2004; Deakin, 2006; Ruffhead, 2020). This transformation is three-dimensional, seven-parameters transformation and can be presented in the form of a relation (Deakin, 1998; Grewal, Weill and Andrews, 2006; Huang and You, 2012):

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} X_0 \\ Y_0 \\ Z_0 \end{bmatrix} + \lambda \cdot A \begin{bmatrix} x \\ y \\ z \end{bmatrix}, \quad (1)$$

where:

- X, Y, Z – coordinates in the primary reference system,
- x, y, z – coordinates in the secondary reference system,
- X_0, Y_0, Z_0 – the translation vector (shift of the primary to secondary coordinate system),
- λ – the scale factor.

$$A = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos\omega & \sin\omega \\ 0 & -\sin\omega & \cos\omega \end{bmatrix} \begin{bmatrix} \cos\varphi & 0 & -\sin\varphi \\ 0 & 1 & 0 \\ \sin\varphi & 0 & \cos\varphi \end{bmatrix} \begin{bmatrix} \cos\kappa & \sin\kappa & 0 \\ -\sin\kappa & \cos\kappa & 0 \\ 0 & 0 & 1 \end{bmatrix}, \quad (2)$$

where:

- ω – the roll angle – rotation (clockwise) around the X axis,
- φ – the pitch angle (anticlockwise) – rotation around the Y axis,
- κ – the yaw angle (clockwise) – rotation around the Z axis,
- $a_{11}, a_{12}, a_{13}, \dots, a_{33}$ – factors of the A – rotation matrix.

In transformation (1), the sequence of transformations has been assumed as: rotation, scale, translation – what in symmetric transformations can be adopted freely. The order of the rotations in matrix A (2) is also conventional and assumed according to photogrammetry order (Zhang, 2010; Luhmann *et al.*, 2014). In rotation matrix various angle systems can be used, e.g. Euler, Tait-Brian as well as quaternions (Titterton and Weston, 2004; Diebel, 2006; Allgeuer and Behnke, 2018). Special applications of transformation by similarity (1) (also for big rotation angles) take place, among others, in the transformation of point clouds (Brazeal, 2013), sensor orientation (Śtepień, 2018), and in 3D modelling accuracy assessment (Brazetti and Scaioni, 2009).

In practice, when it is necessary to apply the transformation of a plane into another plane, e.g. for cadastral purposes in local reference systems (Mataija, Pogarčič and Pogarčič, 2014), the transformation (1) is parameterized and converted into a projective transformation (Seedahmed and Habib, 2002; El-Ashmawy, 2015), what can be written in the form of:

$$X = \frac{Ax+By+C}{Dx+Ey+1},$$

$$Y = \frac{Fx+Gy+H}{x+Ey+1}, \quad (3)$$

where:

- A, B, C, D, E, F, G, H – transformation factors from the image coordinate system (x, y) to the terrain coordinate system (X, Y) .

Transformations (1) and (3) are also parameterized for different scale factors (for each axis – affine transformation) (Sawhney, 1994; Andrei, 2006). Transformations is also commonly used in close range photogrammetry for big (non infinitesimal) rotation angles (Chen, Shen and Liu, 2004; Jue, 2008). This approach is commonly used especially in transformations of data coming from non-metric cameras mounted on UAV and industrial cameras, including cameras with unknown parameters of internal orientation (Colomina and Molina, 2014; Kolecki *et al.*, 2020).

2.1. Research area of CCTV Camera

The analysis of dangerous events in the years in the area of the Odra river near the Szczecin agglomeration In Poland, on the section from the town of Ognica to the border with sea waters, clearly indicates that the highest number of events are collisions of vessels with bridges. When we consider the number of dangerous incidents with bridges divided into individual bridges in the lower section of the Oder River, it results from the analysis that the highest number of incidents are collisions with the Długi and Kolejowy bridges near the railway main station in Szczecin (Kujawski and Stępień, 2017).

CCTV camera used in this researches is mounted on Długi bridge and indicates the shipping area of the Western Oder in Szczecin (Figure 3). The image (camera) parameters and the applied components are presented in Table 1.

Figure 3. Visibility area of CCTV camera on the Długi Bridge towards Kolejowy Bridge in Szczecin

The video material used for the analysis comes from a CCTV camera, with fixed focal length, transmitting 1280x720 px resolution images with AVC (Advanced Video Coding) compression. In order to reduce the data rate, the Inland Navigation Office decided to reduce the frame rate to 4 and the total bit rate was 1059 kb/s.

Table 1. Specification of used CCTV camera

Technical data	FAC 7864
Sensor:	1/3" Progressive Scan CMOS, 1.3MP, 120dB WDR
Max resolution:	1280 × 960
Photosensitivity:	Color: 0.01 lux@F1.2, AGC ON B/W: 0.001 lux@F1.2, AGC ON
Day, night mode:	Yes, IR filter
Auto White Balance (°K):	AWB1:3500-9500,AWB2:2500-15000
Shutter:	1/25s bis 1/100,000s
Wide Dynamic Range:	120dB
Video compression:	H.264 / MJPEG / MPEG4
Network Protocols:	TCP/IP, HTTP, DHCP, DNS, DDNS, RTP/RTSP, SMTP, NTP, SNMP, FTP, QoS, HTTPS, 802.1x
Dimensions (LxWxH):	68 × 64.9 × 144.8 mm

Such a compressed image was characterized by high degradation of the image and a decrease in the number of details, especially for objects located far from the camera. However, during the transformation of the image it was not a problem. The transformation of the image obtained from the Sony Alpha 7M2 digital camera (single frame) was simulated. The image was recorded in a lossless file (RAW) and transformed to rectify the examined points. No differences were noticed during the experiment because the coordinates of the image transformed points are represented in pixels.

In order to avoid ambiguity in the indication of GCP points, each of them was indicated manually tenfold in the image, what resulted in the error of point indication at the level of 0.3 pixel (calculated as mean error of the arithmetic average of ten indications of the point). Thanks to such an approach, this had no significant impact on further calculations. All GCP points were also measured in the field by GNSS receiver with RTK corrections in 20 measurement epochs. The standard deviation on GCP points measured in the terrain was 3 cm (refers to the xy position), which was the value of about 5% to 20% pixel size (GSD) and depends on the distance from the camera.

The experiment concerns the real environment, more specifically the section of the Western Oder river near to the city of Szczecin in Poland. The existing infrastructure is mainly cameras installed on bridges by the Inland Navigation Office in Szczecin and one of the cameras located on the Długi Bridge was the subject of the experiment. The actual image from the camera is shown in Figure 2. The camera captures the image of passing vessels, inland navigation in the crucial point of the Oder River. One of the passages was used in an experiment to determine the actual position of a ship using only the image from an industrial camera.

As we can see in Figure 3, the limited field of view of the camera caused that GCP points (possible to measure) could not be located at the edges of the image. As a result, a significant part of the area in the picture is outside the area covered by GCP points. A significant research problem turned out to be the location of the camera in a place difficult to access (the mast on the bridge), so it was also not possible to carry out a full calibration process of the camera in laboratory conditions using the calibration sheets.

2.2. Algorithm of coordinate transformation

A functional model of position determination based on the projective transformation written by equation (3) was applied. The transformation coefficients A,..., H include the elements of the internal and external orientation of the measurement camera, and equation (3) is based on the transformed equation by similarity (1), where the equations for the X and Y coordinates have been divided by the equation for the Z coordinate (where Z is a constant value for the plane). In the presented approach, the transformation coefficients take the form of equations (4):

$$\begin{aligned}
 A &= \frac{[(Z - Z_0)a_{11} + X_0a_{31}]}{a_{33}(-C_k)}, \\
 B &= \frac{[(Z - Z_0)a_{12} + X_0a_{32}]}{a_{33}(-C_k)}, \\
 C &= \frac{[(Z - Z_0)a_{13} + X_0a_{33}]}{a_{33}(-C_k)}, \\
 D &= \frac{a_{31}}{a_{33}(-C_k)}, \\
 E &= \frac{a_{32}}{a_{33}(-C_k)}, \\
 F &= \frac{[(Z - Z_0)a_{21} + Y_0a_{31}]}{a_{33}(-C_k)}, \\
 G &= \frac{[(Z - Z_0)a_{22} + Y_0a_{32}]}{a_{33}(-C_k)}, \\
 H &= \frac{[(Z - Z_0)a_{23} + Y_0a_{33}]}{a_{33}(-C_k)}.
 \end{aligned} \tag{4}$$

And after considering equation (2) the form developed into equations (5):

$$\begin{aligned}
A &= \frac{[(Z - Z_0)\cos\varphi \cos k + X_0 (\sin\omega \sin k + \cos\omega \sin\varphi \cos k)]}{(\cos\omega \cos\varphi)(-C_K)}, \\
B &= \frac{[(Z - Z_0)(\cos\varphi \sin k) + X_0 (\cos\omega \sin\varphi \sin k - \sin\omega \cos k)]}{(\cos\omega \cos\varphi)(-C_K)}, \\
C &= \frac{(Z - Z_0)(-\sin\varphi) + X_0 \cos\omega \cos\varphi}{\cos\omega \cos\varphi}, \\
D &= \frac{\sin\omega \sin k + \cos\omega \sin\varphi \cos k}{\cos\omega \cos\varphi(-C_K)}, \\
E &= \frac{\cos\omega \sin\varphi \sin k - \sin\omega \cos k}{\cos\omega \cos\varphi(-C_K)}, \\
F &= \frac{(Z - Z_0)(\sin\omega \sin\varphi \cos k - \cos\omega \sin k) + Y_0(\sin\omega \sin k + \cos\omega \sin\varphi \cos k)}{\cos\omega \cos\varphi(-C_K)}, \\
G &= \frac{(Z - Z_0)(\cos\omega \cos k + \sin\omega \sin\varphi \sin k) + Y_0(\cos\omega \sin\varphi \sin k - \sin\omega \cos k)}{\cos\omega \cos\varphi(-C_K)}, \\
H &= \frac{(Z - Z_0) \sin\omega \cos\varphi + Y_0 \cos\omega \cos\varphi}{\cos\omega \cos\varphi}.
\end{aligned} \tag{5}$$

The determination of the transformation coefficients A,..., H for the four adjustment points (common points) is unambiguous. In presented method they were determined for four, five and six adjustment points, where the fifth and sixth points are virtual points on the water. A variant of coordinate transformation based only on virtual points on water, without fixed points on land, was also tested. In the case of a redundant number of adjustment points, the transformation coefficients were determined using the method of least squares, by means of equation (6).

$$\begin{bmatrix} -X_1 \\ -Y_1 \\ -X_2 \\ -Y_2 \\ \dots \\ -X_n \\ -Y_n \end{bmatrix} = \begin{bmatrix} -x_1 & -y_1 & -1 & 0 & 0 & 0 & X_1 \cdot x_1 & X_1 \cdot y_1 \\ 0 & 0 & 0 & -x_1 & -y_1 & -1 & Y_1 \cdot x_1 & Y_1 \cdot y_1 \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ -x_n & -y_n & -1 & 0 & 0 & 0 & X_n \cdot x_n & X_n \cdot y_n \\ 0 & 0 & 0 & -x_n & -y_n & -1 & Y_n \cdot x_n & Y_n \cdot y_n \end{bmatrix} \times \begin{bmatrix} A \\ B \\ C \\ F \\ G \\ H \\ D \\ E \end{bmatrix}, \tag{6}$$

where:

$$X = (A^T \cdot A)^{-1} \cdot A^T \cdot L.$$

The locations of the points used for the camera transformation and calibration, including the virtual points - located on the water, are shown in Figure 4.

Figure 4. Location of points used for coordinate transformation and camera calibration, including virtual points (points on water) - visualization on the basis of 3d scanner image

Camera calibration coefficients were applied according to Brown's model (Brown, 1966) (7).

$$\begin{aligned} x' &= x + \bar{x} \cdot (K_1 \cdot r^2 + K_2 \cdot r^4 + K_3 \cdot r^6 + \dots) + [P_1 \cdot (r^2 + 2 \cdot \bar{x}^2) + 2 \cdot P_2 \cdot \bar{x} \cdot \bar{y}] \\ &\quad \cdot [1 + P_3 \cdot r^2 + \dots], \\ y' &= y + \bar{y} \cdot (K_1 \cdot r^2 + K_2 \cdot r^4 + K_3 \cdot r^6 + \dots) + [2 \cdot P_1 \cdot \bar{x} \cdot \bar{y} + P_2 \cdot (r^2 + 2 \cdot \bar{y}^2)] \\ &\quad \cdot [1 + P_3 \cdot r^2 + \dots]. \end{aligned} \quad (7)$$

Parameters of radial distortion r and decentring distortion as well as corrections to the camera fixed length and principia point are determined by least squares method using equation (8).

$$\begin{bmatrix} x_1 - x_{1calc} \\ y_1 - y_{1calc} \\ x_2 - x_{2calc} \\ y_2 - y_{2calc} \\ \dots \\ x_n - x_{ncalc} \\ y_n - y_{ncalc} \end{bmatrix} = \begin{bmatrix} \bar{x}_1 \cdot r_1^2 & \bar{x}_1 \cdot r_1^4 & \bar{x}_1 \cdot r_1^6 & r_1^2 + 2 \cdot \bar{x}_1^2 & 2 \cdot \bar{x}_1 \cdot \bar{y}_1 & x_{1calculated} & 1 & 0 & 0 \\ \bar{y}_1 \cdot r_1^2 & \bar{y}_1 \cdot r_1^4 & \bar{y}_1 \cdot r_1^6 & 2 \cdot \bar{x}_1 \cdot \bar{y}_1 & r_1^2 + 2 \cdot \bar{y}_1^2 & y_{1calculated} & 0 & 1 & 0 \\ \bar{x}_n \cdot r_n^2 & \bar{x}_n \cdot r_n^4 & \bar{x}_n \cdot r_n^6 & r_n^2 + 2 \cdot \bar{x}_n^2 & 2 \cdot \bar{x}_n \cdot \bar{y}_n & x_{ncalculated} & 1 & 0 & 0 \\ \bar{y}_n \cdot r_n^2 & \bar{y}_n \cdot r_n^4 & \bar{y}_n \cdot r_n^6 & 2 \cdot \bar{x}_n \cdot \bar{y}_n & r_n^2 + 2 \cdot \bar{y}_n^2 & y_{ncalculated} & 0 & 1 & 0 \end{bmatrix} \cdot \begin{bmatrix} K_1 \\ K_2 \\ K_3 \\ P_1 \\ P_2 \\ \Delta c_k \\ \Delta x_0 \\ \Delta y_0 \end{bmatrix}, \quad (8)$$

where

$$X = (A^T \cdot A)^{-1} \cdot A^T \cdot L.$$

The calculation diagram of the proposed method is shown on Figure 5.

Figure 5. The scheme of transformation with the application of centres of gravity (mass)

The proposed calculation method (Figure 5) is based on geodetic data measured by a GNSS RTK receiver. Ground Control Points - GCPs are measured with the use of RTK (Real Time Kinematic) corrections, and Independent Control (Check) Points - ChPs are the positions of virtual points (marks installed and surveyed on floating boat with GNSS receiver). The coordinates of GCP and ChP points measured by a GNSS receiver are represented in a coordinate system PL-2000 (EPSG 2176) for the area concerned.

In presented method the projective transformation is performed in several stages. Separately for the coordinates located inside the area defined by the reference points and separately for the other points.

The second method uses fixed quay points and virtual points lying on the water surface. Virtual points are included gradually as the transformation area increases. The VP5 point is added first and the points inside the area including the fixed points and the VP5 point are transformed. Then another point VP6 is added and points inside the area bounded by the fixed points and VP5 and VP6 are transformed. In the next step, after the projection transformation is completed, a quasi-similarity transformation (Q-ST) is performed for the entire set of points, which provides a control mechanism for the previous calculation.

The Q-ST transformation model is a modified transformation by similarity that produces more accurate results compared to the traditional transformation by similarity method for a small number of adjustment points. The Q-ST transformation uses a least squares method that is applied sequentially – separately to each of the calculation steps (scale factor, translation, rotations). Before calculating the quasi rotation matrix (rotation matrix with affine scale adjustments), the coordinate systems are shifted to the centres of gravity. The Q-ST transformation model is described in (Stępień *et al.*, 2020) and is represented by the formula:

$$X_{TF} = R \cdot (\lambda \cdot X_{LF} - X_{CLF}) + X_{CTF} = R \cdot \left[(D_{LF}^T \cdot D_{LF})^{-1} \cdot D_{LF}^T \cdot D_{TF} \right] \cdot X_{LF} - \frac{\sum_{i=1}^N (X_{iLF})}{n} + X_{CTF}, \quad (9)$$

where:

- X_{TF} – coordinates in the target system – stationary (target reference frame – TF),
- R – rotation matrix,
- λ – scale factor,
- X_{LF} – coordinates in the transformed system (local reference frame – LF),
- X_{CLF} – coordinates of the center of gravity in the transformed system (centroid of local reference frame),
- X_{CTF} – coordinates of the center of gravity in the target coordinate system,
- D_{TF} – vector length in the transformed coordinate system (TF),
- D_{LF} – the length of the vector in the local coordinate system (LF).

In this method, a variant of the projective transformation based only on virtual points, without fixed points distributed on land, is also tested (points 1-14 on Figure 4).

3. Results

The results section presents the results of the measurement experiment. Calculations with use of traditional Projective transformation algorithm and with use of SPT transformation are compared. SPT transformation calculations were performed according to the algorithm presented in section 2.2. In one of the variants, only virtual control points (VCP) located on the water were used for calculations. Ground Control Points (GCP) were measured using a GNSS receiver with RTK corrections. The coordinates of GCPs and VCPs that were used in each transformation variant are summarized in Table 2.

Table 2. Coordinates of GCP and VCP in camera and terrain coordinate system

GCP	VCP	Image coordinates		PL-2000 coordinates (EPSG 2176)	
		X [pix]	Y [pix]	X [m]	Y [m]
118	-	417	1221	5921149.44	5470599.74
104	-	364	1046	5921085.67	5470513.18
L	-	337	336	5920986.09	5470516.27
P	-	340	687	5921006.75	5470471.20
-	VP5	629	891	5921192.13	5470698.05
-	VP6	391	796	5921108.45	5470586.86
-	1	100	577	5921004.863	5470560.776
-	9	137	559	5921082.779	5470629.883
-	5	134	1227	5921073.443	5470515.696
-	7	126	898	5921062.442	5470565.436
-	12	259	1482	5921182.539	5470661.491
-	14	294	99	5921166.733	5470727.112

Based on the data collected in Table 2, transformation coefficients were calculated using equation (6). Corrections to the coordinates due to distortion were calculated using equation (8), and the Q-ST transformation was performed using equation (9). Table 3 shows the calculated transformation coefficients using different computational options.

Table 3. Projective and Sequential Projection Transformation (SPT) coefficients

Coefficients	Projective					SPT	
	4 GCP	3 GCP, 1 VCP	4 VCP	5 VCP	6 VCP	4 GCP, 1 VCP	4 GCP, 2 VCP
A	0.115819	0.125327	-0.008431	-0.917657	-1.033548	0.125766	-1.044864
B	0.067129	0.072367	0.014919	0.004734	0.002816	0.071237	0.034071
C	-170.560163	-171.436750	-24.904558	29.664812	29.207469	-171.284099	41.446555
D	-0.013204	-0.013062	-0.002022	-0.006612	-0.007133	-0.013078	-0.007417
E	-0.000207	-0.000226	-0.000103	-0.000341	-0.000365	-0.000220	-0.000207
F	0.307404	0.290749	-0.006562	-1.030018	-1.170367	0.291894	-1.390788
G	-0.066844	-0.062112	-0.011422	-0.088444	-0.098365	-0.063398	-0.057613
H	-218.744743	-219.209455	-32.563321	38.059352	37.590645	-219.040959	49.649679

The transformation coefficients collected in Table 3 take on similar values when a similar set of scores was used to calculate them. Two groups of similar score values can be seen. The first group is the results in columns 1, 2 and 6, the second group is the results obtained in columns: 3, 4, 5 – where transformations were performed based only on virtual points located on the water. Different from both groups coefficients of transformation were obtained when 4 GCP points and 2 VCP points were used for transformation (column 7). In this variant one point (VP6) was used for transformation, which was not present in any of the other transformation variants. The transformation errors on the GCP/VCP points are shown in Table 4.

Table 4. Accuracy at GCP and VCP control points

GCP/VCP	Mean Errors (standard deviations at GCP/VCP control points)		
	σ_{0X} [m]	σ_{0Y} [m]	σ_{0XY} [m]
4 GCP	0.00	0.00	0.00
3 GCP, VCP	0.00	0.00	0.00
4 VCP	0.00	0.00	0.00
5 VCP	0.62	0.85	1.05
6 VCP	0.82	1.15	1.14
4 GCP, VCP	0.10	0.15	0.18
4 GCP, VCP	1.82	2.29	2.93

The Projective transform is significant for four adjustment points, as confirmed by the results collected in Table 4. Thus, the mean errors (standard deviations) equal zero. In the case where the number of points is five or six these errors are no longer zero. The results presented show that the errors on the GCP/VCP control points are smaller each time when five adjustment points are used, regardless of their configuration (4 GCP and 1 VCP or 5 VCP). With six adjustment points (common points), these errors are higher, but to have a comprehensive picture of the accuracy analysis, these errors must be considered together with the errors on the control points (Table 5). Table 5 shows the errors on the control points separately for points inside the transformation area (interpolation) and separately for points outside the transformation area (extrapolation).

Table 5. Comparison of accuracy at ChP control points

Transformation variant	Mean Errors (standard deviations at GCP/VCP control points)	
	Inside GCP/VCP (interpolation)	Outside GCP (extrapolation)
	σ_0 [m]	σ_0 [m]
4 GCP	3.89	8.56
3 GCP, 1 VCP	3.52	8.46
4 VCP	2.95	-
5 VCP	3.78	-
6 VCP	3.68	-
4 GCP, 1 VCP (SPT)	3.55	8.56
4 GCP, 2 VCP (SPT)	6.55	4.68

The results of the calculations collected in Table 5 and Table 6 show that the deviations at the ChP control points are in the precision range of the GNSS receiver mounted on the barge (navigation class without RTK correction).

Figure 6. Error ellipses for selected variants

As can be noticed after Table 4 analysis, the accuracy on control points in the method used in this publication increases in relation to the standard applied projective transformation. A view of all ChP points is shown on Figure 7.

Figure 7. Results of transformations compared to GNSS data

4. Discussion

The analysis of the results presented in Tables 4 and 5 shows that including virtual points in the calculations increases the accuracy both for GCP/VCP points and for ChP. High accuracy for GCP/VCP

points is particularly evident when their number is five – the error is then within 1 m. On the other hand, when another virtual point VCP is added, the accuracy on GCP/VCP points decreases, but at the same time the accuracy on ChP control points increases, especially in the area that was previously outside the GCP/VCP points.

The increase in accuracy on the ChP control points is almost double, while the accuracy on the GCP/VCP points deteriorates at a similar level (almost double). This shows that the Sequential Projection Transformation (SPT) significantly improves the accuracy on the control points, while decreasing the accuracy on the alignment points (common points). The sequential inclusion of control points is therefore intended to improve accuracy on points that are not used in the transformation – ultimately resulting in a significant improvement in the accuracy of the vessel's position in the areas where it is currently located. Virtual points scale the transformation area and improve accuracy in the areas where they are located. At the same time, the accuracy on the adjustment points decreases and becomes closer to the accuracy of the control points. The proposed method balances the accuracies in the sequentially added areas and causes their significant increase (in the conducted experiment, the accuracy almost doubled). At the same time, it should be emphasized that the inclusion as an additional step of the Q-ST transformation does not significantly improve the accuracy of control points (ChP). In the conducted experiments, the improvement of accuracy, after additional application of Q-ST transformation, was found at the level of 0.01-0.05 m. This is insignificant compared to the accuracy obtained at the control points. Q-ST transformation in combination with projective or SPT transformation can be treated as "smoothing of the results" and at the same time as an independent control method of calculations (similar – almost identical – accuracy as in projective or SPT transformation can be expected).

The achieved accuracy confirms the validity of the approach. In the presented difficult conditions of inland navigation, with an unfavourable field of view of a single non-metric measuring camera and with an approximate plane of GCP and ChP points, satisfactory results have been achieved. These results are improved about 100 % compared to an approach based only on a projection transformation and carried out under the same difficult measurement conditions.

5. Conclusions

The proposed method, can be used to assist in determining the position of vessels using AIS system, and also in the absence of this system or limitations in the availability of GNSS signal. The method can also find application in the off-shore industry for positioning objects on water when there are no reference points around and navigation systems are disturbed or inoperative. The method also enables calibration of non-metric cameras under measurement conditions when there are no fixed reference points in the field.

The proposed calculation approach is simple and quick to apply and can be applied under difficult observation conditions and unfavourable distribution of GCP control points. In the case of CCTV cameras, the good GCP control points on which the transformations can be based are the mooring bitts. Therefore, it is advisable to place the cameras in such a way that the mooring bitts on both sides of the river cover the largest possible field of view of the camera. will further improve the positional accuracy of floating objects in inland navigation and further exploit the advantages of the proposed transformation model.

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