**ICCEPM 2024** https://dx.doi.org/10.6106/ICCEPM.2024.0570
The 10th International Conference on Construction Engineering and Project Management
*Jul. 29-Aug.1, 2024, Sapporo*

# Dimension extraction technique for structures using point cloud data

Jehee Han[1]*, Minseo Jang[2], SungKwon Woo[3], Do Hyoung Shin[4]

[1] *Department of civil engineering, Inha University, Republic of Korea,* E-mail address: hjh239614@gmail.com
[2] *Department of civil engineering, Inha University, Republic of Korea,* E-mail address: mjang@inha.ac.kr
[3] *Department of civil engineering, Inha University, Republic of Korea,* E-mail address: skwoo@inha.ac.kr
[4] *Department of civil engineering, Inha University, Republic of Korea,* E-mail address: dshin@inha.ac.kr

**Abstract:** Recently, digitalization technologies for data analysis have become a global issue. As a result, in the construction market, Building Information Modeling (BIM), which is a core technology of smart construction, is being actively utilized not only in the architectural sector but also in the civil engineering field worldwide. In this study, the process of creating BIM models using a 3D scanner is examined, and automated extraction of numerical information for infrastructures necessary for library creation is conducted. In experiments utilizing infrastructurs such as retaining walls and employing algorithmic methods, the accuracy of cross-sectional numerical information for each retaining wall was confirmed to be over 95%. This enables not only BIM modeling but also the generation of drawings for facilities lacking BIM drawings by confirming the shape information of infrastructures, thus facilitating efficient maintenance.

**Key words:** BIM, Point Cloud Data(PCD), Management, Automation

## 1. Introduction

As 3D LiDAR technology rapidly advances worldwide, Scan-to-BIM becomes an essential element from the perspective of construction maintenance. Consequently, there is a need for technology to automatically process 3D point cloud data acquired via LiDAR. While various technologies exist for automatic processing of 3D point cloud data, segmentation techniques dominate the field. However, it has been observed that there is a lack of research on methods for automatically extrsacting numerical information for each component from point cloud data after segmentation.
Therefore, this paper aims to describe the RANSAC algorithm for segmenting virtual retaining wall point cloud data and explain techniques for automatically extracting numerical information for classified components.

## 2. Analysis method

In order to automatically obtain numerical information about infrastructure facilities, appropriate segmentation for each member is required, a method of obtaining outlines from point cloud data, and an orthographic projection method are needed. I will explain this method in detail.

### 2.1. RANSAC

Extracting features from massive unstructured point cloud data with varying densities is a challenging task. However, using RANSAC (RANdom Sample Consensus), it is possible to remove noise based on the shape of clustered point cloud data and predict the shape that best represents the

characteristics of the point cloud data. Therefore, research on RANSAC, which can handle various forms of point cloud data, continues[1].
For example, RANSAC algorithms have been developed for classifying roof point cloud data obtained through airborne laser scanners[4]. The Seq-NV-RANSAC algorithm addresses the limitations of RANSAC to classify parallel and incremental planes of stairs effectively[2]. Additionally, RANSAC-based algorithms, such as cylinder detection, can detect curved surfaces commonly found in pipes or trusses[3].

### 2.1.1 RANSAC Feautures

RANSAC has the characteristic of ignoring data above a certain threshold set by the user, thus finding the ideal model that best matches the maximum data without reflecting noise. In this context, the threshold is the distance from arbitrarily set lines, planes, or structures, and point cloud data beyond this threshold are considered outliers, while data within the threshold are considered inliers. Here, the objective is to derive the predominant shape, such as a line, plane, or structure, based on the highest number of inliers within the threshold.

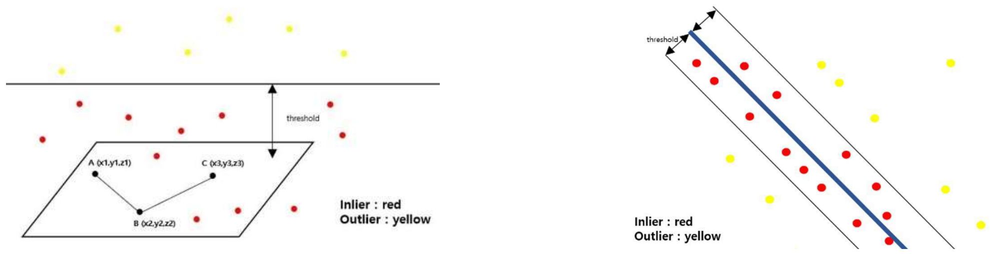



**Fig. 1.** Example of the optimal plane and line using RANSAC.

The number of iterations (N) performed by the RANSAC algorithm to derive the target plane is determined by the following equation.

$$N = \frac{\log(1-P)}{\log(1-(1-E)^S)} \tag{1}$$

Here, **P** represents probability, **S** represents the number of data points, and **E** represents the ratio of inliers to outliers. In other words, when determining how effective it is to repeatedly derive the target shape by randomly selecting two or three points, one can assume the probability (**P**) and the ratio of outliers to inliers (**E**), and assume the number of data points (**S**) required to form a minimal set. Additionally, one can decide how precisely to derive the target shape through a threshold value.
The number of iterations (**N**) performed by the RANSAC algorithm is determined based on these parameter values. By adjusting how these parameters are set, the algorithm iterates **N** times, and with each iteration, the inliers become sufficiently defined, allowing for the derivation of the most suitable shape as the target shape.

### 2.1.2 RANSAC (Plane) result

In this study, we applied the RANSAC algorithm to both synthetic virtual retaining wall point cloud data and actual scanned retaining wall data. When applying the RANSAC algorithm, we derived the optimal plane for the points located on each face of the retaining wall. Additionally, considering the density of the point cloud data, we specified that the minimum number of points required to form a plane is 1000, thereby determining the number of planes generated based on the density of the data. As a result, for the virtual retaining wall data, 13 planes were derived.

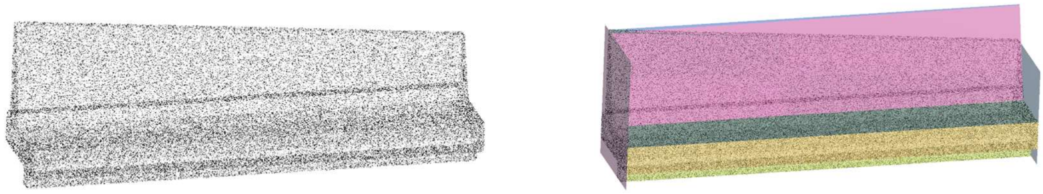


**Fig. 2.** Virtual retaining wall data

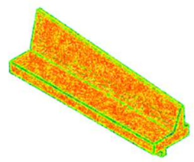
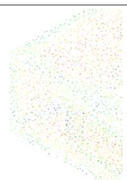
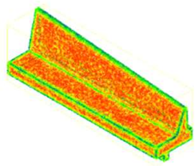
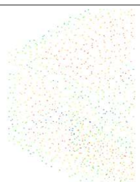
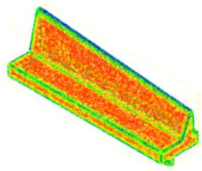
**2.2. Edge Detection**

To extract the length and positional information of structures, it is essential to utilize information from unstructured and unaligned point cloud data located on the contours of the structures. While research on extracting line features from 2D images and representing them as 3D lines has been actively pursued in image-based tasks, studies on extracting contour lines from 3D point cloud data with significantly varying point densities and irregular neighbor structures are rare. In this chapter, we describe a method for automatically detecting lines with rapidly changing surface directions in point clouds of infrastructures.

**2.2.1 Edge Detection result**

The points located on the contours represent lines exhibiting abnormal discontinuities in the progression direction of the point cloud. In this chapter, we quantify and represent the planarity characteristic through the geometric structure of neighboring points relative to an arbitrary point in the point cloud. The parameter influencing the degree of planarity is the density of points and the distance to neighboring points. The following table demonstrates the degree of planarity while keeping the distance to neighboring points fixed and varying the density of points, as well as while keeping the density of points fixed and varying the distance to neighboring points.

**Table 1.** Degree of virtual retaining wall outline adjusting parameters

| Radius=0.3<br>varying the density of points based on space | | the density of points = approximately 150,000<br>varying the distance to neighboring points | |
|---|---|---|---|
| min. space = 0.2 |  | Radius = 0.25 |  |
| min. space = 0.4 |  | Radius = 0.35 |  |
| min. space = 0.5 |  | Radius = 0.4 |  |

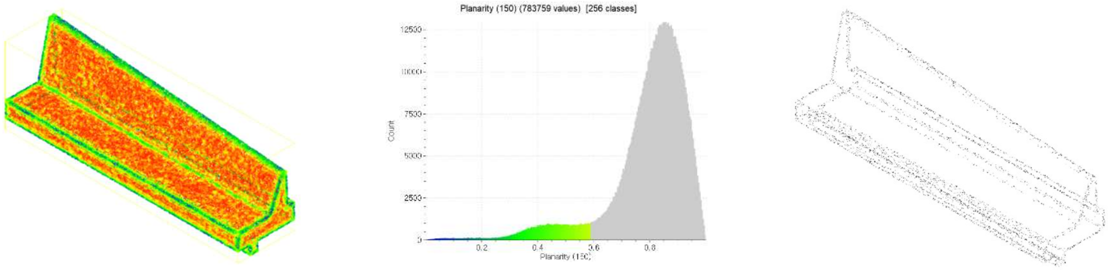



**Fig. 3.** the outline of a retaining wall

By varying the density of points and the radius, we derived the optimal contour lines. In our study, for virtual retaining wall data, we set the radius to 0.35 and the minimum space based on space to 0.2. This resulted in the exclusion of points, except for those in areas where the direction of points changed abruptly, to derive the contour lines.
The derived contour lines, labeled from 1 to 12, are shown in the following figure. These contour lines represent the point cloud from the left perspective of the retaining wall.

### 2.3. Intersection point

To derive the length and positional information of structures, we use the RANSAC algorithm to represent the points located on the contours as equations of 3D lines. We then find the intersections between each pair of lines and calculate their lengths. However, the equations of lines obtained through the RANSAC algorithm represent information in 3D space, increasing the likelihood of each line being located in tangled positions. Therefore, we project the lines obtained through RANSAC onto a single plane of the retaining wall and find their intersections.

#### 2.3.1 RANSAC(Line) result

We applied the RANSAC algorithm to the point cloud data representing the contours of one side of a virtual retaining wall in the form of an inverted T. When applying the RANSAC algorithm, we derived the optimal lines for the points located on each edge of the retaining wall. Additionally, considering the density of the point cloud data and the threshold, the direction of the lines derived is determined. We fixed the threshold at 0.01m and the number of iterations at 1. As a result, for the point cloud data representing the contours of one side of the virtual retaining wall, 12 different lines were extracted.

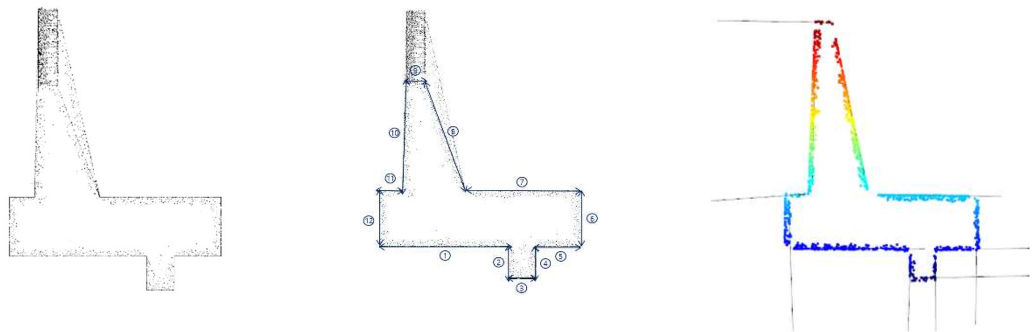


**Fig. 4.** Contour generation with RANSAC

#### 2.3.2 intersection point after projection

The equations of the lines derived through RANSAC (Line) represent lines in 3D space, which increases the likelihood of them being located in tangled positions. Therefore, to find the intersections between lines in 3D space, it is necessary to project the lines generated through RANSAC (Line) onto the planes created through RANSAC (Plane). Each projected line will have one or more intersection points, which can be used to derive the intersection points for each line. Below is the visualization of the intersection coordinates obtained through actual code implementation.

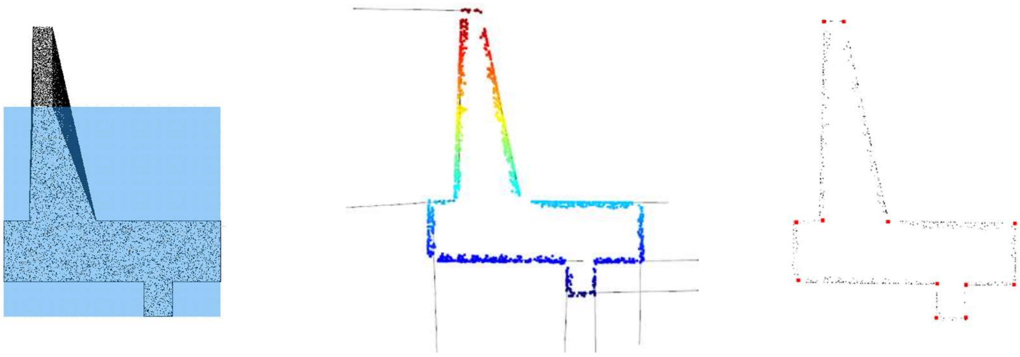


**Fig. 5.** Objection of a side of retaining wall

## 3. Results of analysis

Here are the accuracy based on the results obtained through the method described above for the virtual retaining wall with a counterweight formula. The accuracy of the numerical information is confirmed to be approximately 95% on average.

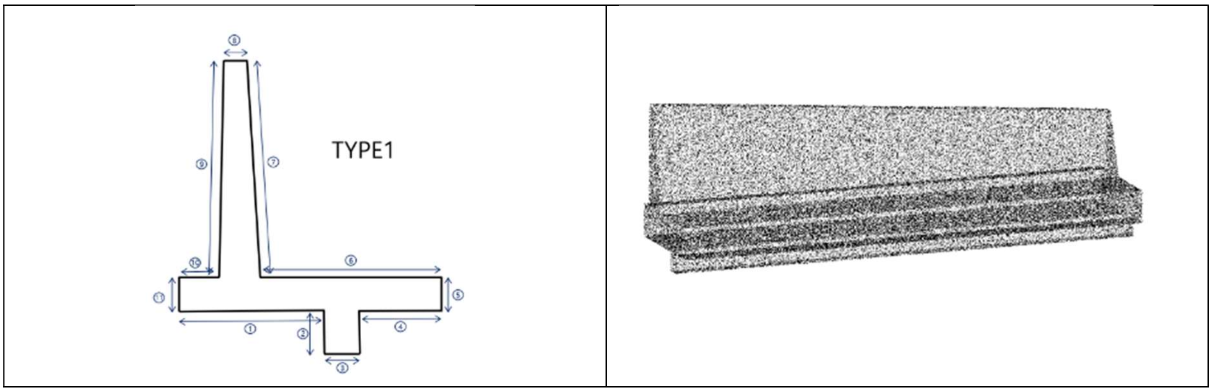



**Fig. 6.** Anti-gravity Type 1 (retaining wall of varying height)

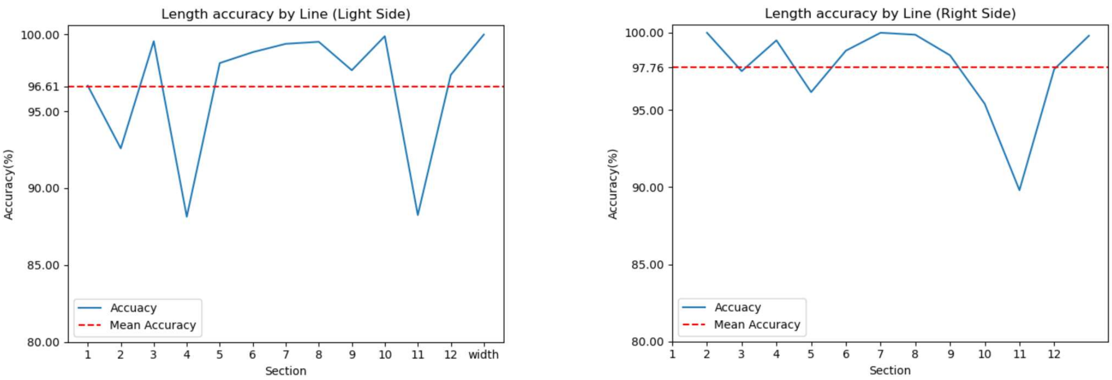



**Fig. 7.** Graph of Length accuracy

The following figure 8. and figure 10. are an inverted t-type retaining wall and a gravity type retaining wall, respectively. Each length information was expressed in a graph to indicate accuracy.s

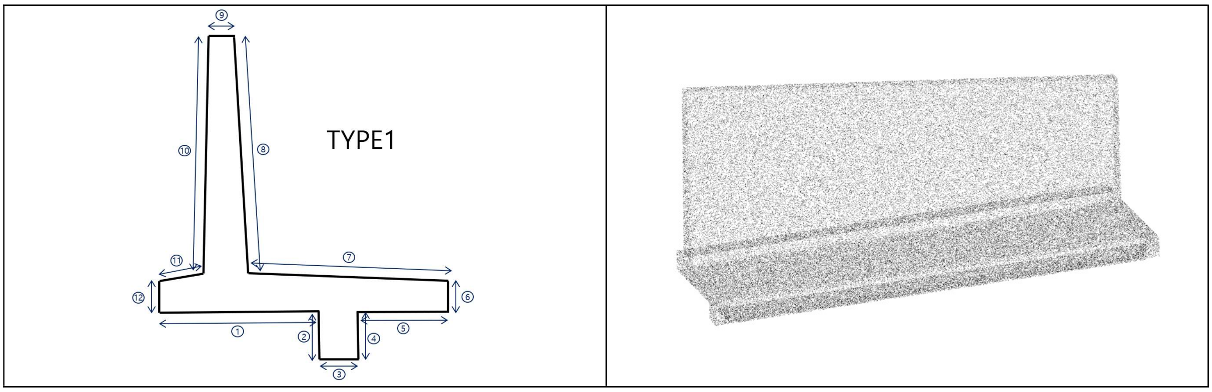



**Fig. 8.** Inverted T Type 1 (retaining wall of varying height)

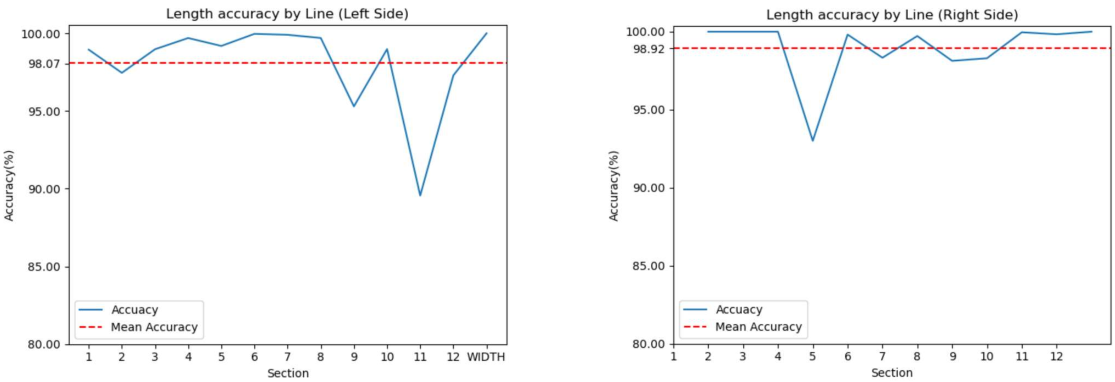



**Fig. 9.** Graph of Length accuracy

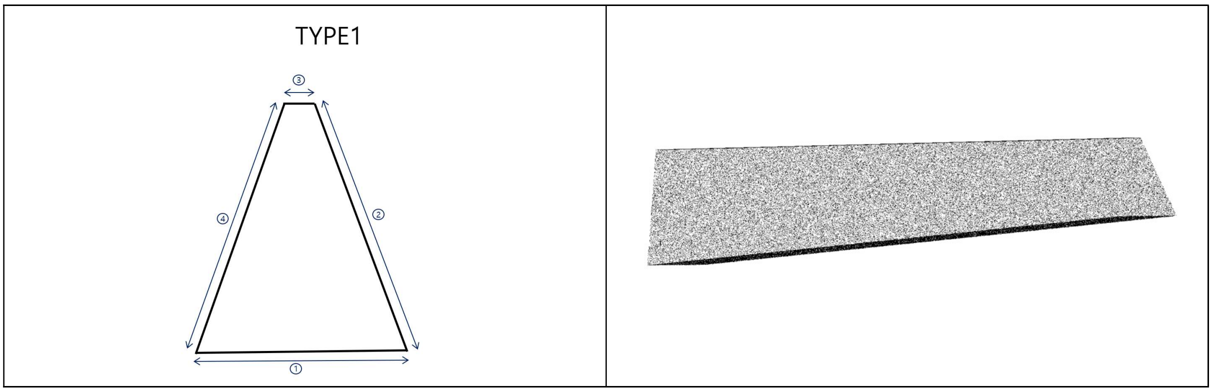



**Fig. 10.** Gravity Type 1 (retaining wall of varying height)

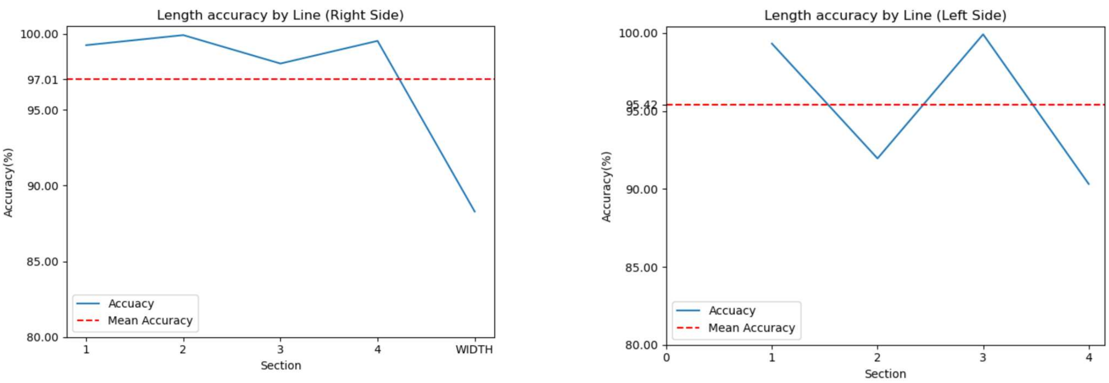



**Fig. 11.** Graph of Length accuracy

## 4. Conclusion

This paper proposes a technique for handling virtual retaining wall point cloud data, focusing on infrastructure facilities. The accuracy of the numerical information for the retaining wall was confirmed to be over 96% across all sections, validating that the automatic numerical extraction technique for retaining walls is measured with high accuracy.
s
However, this method still has some obvious limitations as follows:

1. While it is observed that the accuracy exceeds 90% in most sections, sections 4, 10, and 11 fall short of achieving 90% accuracy. This is likely due to the lack of point cloud data on the contours in shorter sections. Therefore, it is necessary to devise methods to minimize point data loss during the contour generation process.

2. In virtual retaining wall data, it was possible to extract length information by examining all sides. However, in the case of real retaining walls, there may be sections buried in the ground, resulting in unavailable shape information when scanned with lidar. Therefore, it is necessary to devise a method to incorporate length information corresponding to the scanned data based on the standard dimensions of the retaining wall.

By employing these methods to automatically derive numerical information for infrastructures and generating BIM models for infrastructure facilities lacking drawings, time and cost required for maintenance of infrastructure facilities can be reduced.

## 5. ACKNOWLEGEMENTS

The support of the Basic Science Research Program of the National Research Foundation (NRF) funded by the Korean government(MSIT) is gratefully acknowledged. (No.RS-2023-00217983)

## 6. REFERENCES

[1] M.A. Fischler, R.C. Bolles, Random sample consensus: a paradigm for model fitting with applications to image analysis and automated cartography, Commun. ACM 24 (6) 381–395, 1981.

[2] T.M. Awwad, Q. Zhu, Z. Du, Y. Zhang, An improved segmentation approach for planar surfaces from unstructured 3D point clouds, Photogramm. Rec. 25 (129) 5–23, 2010.

[3] D.H. Ballard, Generalizing the Hough transform to detect arbitrary shapes, Pattern Recogn. 13 (2) 111–122, 1984

[4] F. Tarsha-Kurdi, T.Landes, P.Grussenmeyer, hough-transform and extended RANSAC algorithms for automatic detection of 3D building roof planes from LIDAR data. IAPRS, 407-412, 20s08