 DOI: 10.3217/978-3-85125-663-5-35

Machine Vision Solution for a Turnout Tamping Assistance System

Gerald Zauner[1], Tobias Mueller[2], Andreas Theiss[2], Martin Buerger[2], Florian Auer[2]

***Abstract*— In order to guarantee safe and comfortable train travel, the tracks must be in the correct geometric position. For this reason, so-called tamping machines are used worldwide to perform this important task of track maintenance. Turnout-tamping is a complex procedure to improve and stabilize the track situation in turnout-areas, which is usually only carried out by experienced operators. This application paper presents the current state of development of a 3D laser line scanner-based sensor system for a new tamping assistance system, which should support and relieve the operator in complex tamping areas. In this context, semantic segmentation is used to fully automatically identify essential and critical areas in the generated 3D depth images and process them for subsequent machine control.**

I. INTRODUCTION

A. Tamping process

When a train drives along the railway, it generates enormous forces. The entire track consisting of rails, sleepers and ballast is an elastic system that deforms and then returns to its original position. In the end, this high load leads to a deterioration of the track geometry. This can lead to anomalies, because of which the ideal geometry of the track can no longer be guaranteed. In these areas, for example, temporary speed restrictions must be imposed. To avoid such a situation, tracks have to be maintained at regular intervals. This ensures that the ideal geometry of the track is restored. In this context, the so-called track tamping represents the most common maintenance task on railway tracks. Lining refers to correcting the horizontal and vertical alignment of the track, and lifting to the compaction and displacement of the substructure with complete removal of cavities under the sleepers. The combined lifting-lining unit works with a measuring system, gripping the track, raising the track to a predetermined height, correcting for vertical misalignment and simultaneously pivoting the track to correct horizontal alignment. Subsequently, the tamping units are lowered and the tamping tines dip into the ballast. The tamping unit vibrates to fluidize the ballast so that it can rearrange and settle in a dense matrix. Thereafter, the tamping machine moves forward to the next sleeper and the process is repeated. Finally, behind the tamping machine, the result is a track at the correct geometric level, on a homogeneous ballast bed and with restored elasticity [1].

B. Turnout Tamping Assistant

The purpose of the turnout-tamping assistant is to develop an automatic assistance system comparable to level 3 of the SAE J3016 standard (which was originally defined to characterize the autonomous driving of road-bound motor vehicles). Generally, the focus is on the automated support of tamping in difficult environments such as turnout areas and crossings (but not restricted to). At this level of automation, the system creates action recommendations that the operator can confirm prior to each action. The aim is to relieve the operator, to increase the working speed and to stabilize the quality of work at a consistently high level. Basically, the tamping assistance system is also suitable for higher degrees of autonomy [2,3].

[1]Gerald Zauner, School of Engineering, Upper Austria University of Applied Sciences, 4600 Wels, Austria
[2]Plasser & Theurer, Export von Bahnbaumaschinen GmbH, Linz

Fig. 1. Tamping machine with a roof-mounted 3D laser scanner.

II. 3D DEPTH IMAGE ACQUISITION

A. Relevant object information from 3D scanner image data

The environment (i.e., mainly the superstructure directly in front of the tamping machine) is scanned with a rotating 3D laser scanner mounted on the tamping machine roof (Fig.1). The scanner itself delivers single line scans with millimeter depth accuracy, which are then continuously merged into a depth image with a typical resolution of approximately 4000 x 1000 pixels, where different gray values correspond to different distances to the sensor (i.e. the brighter the image pixels, the closer). The scanner head is mounted in front of the train whereas the actual tamping unit is located approximately in the middle of the machine. Thus, due to moving of the vehicle, there is a small time offset between the scanning of a certain region and the actual tamping process at this particular position, which provides a time window of about 10 seconds for all necessary data processing tasks. Additionally, the raw line scans have to be geometrically corrected as the scanning laser spot moves in a helix-like trajectory along the railway tracks. This correction is of course speed-dependent. The actual working speed during tamping is approx. 1000m/h, which leads to a lateral scan resolution of approx. 2mm. This is sufficient to create detailed scan images that allow visualization even of small objects (such as fasteners, etc., Fig.2).

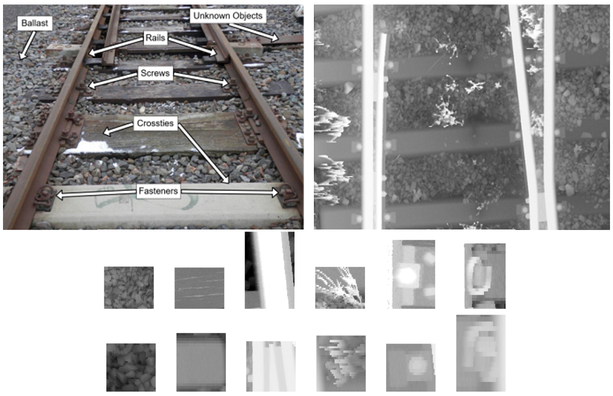

Fig. 2. Picture of the relevant track area (top); typical 3D scan depth image (middle); 3D scan image patches (bottom).

III. Semantic Segmentation of 3D-Scanner Data

Semantic segmentation generally plays a crucial role in computer vision and enables a computer to not only recognize objects in images, but also to locate them pixel-exactly. The recognition and exact delineation of objects in the image is achieved by the classification of each individual pixel, i.e. each pixel is assigned a defined object class (Fig.3). Our original segmentation approach was based on a Fully Convolutional Network (FCN) [4], a popular algorithm for semantic segmentation.

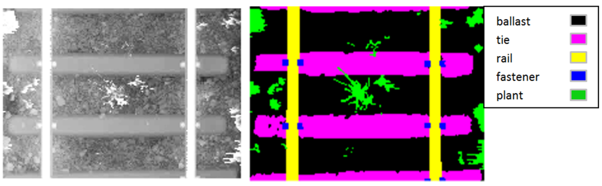

Fig. 3. 3D scanner image (left). Desired result image (right) with pixel-exactly segmented areas representing the relevant image contents such as ballast, rails, plants, etc.

A general challenge in deep learning is the large amount of learning data needed to produce good results i.e. enough annotated images must be provided to train the network. Especially, in semantic segmentation the according effort is considerable, since a pixel-precise marking of the image objects is necessary. A further challenge is the fact that we have to deal with a very imbalanced dataset. The images typically consist of large areas of ballast structures whereas e.g. only very few pixels represent objects like rail screws. Besides real world data we also used artificially generated depth images from a virtual simulation environment (this simulator was originally intended for machine operator training purposes thus providing very realistic 3D scenarios). In this case, no manual labelling of the images was necessary and we were able to provide large quantities of images very quickly (and we could even vary image structures specifically, such as different gravel sizes, etc.). Furthermore, with the help of the simulator, we were also able to intensively test and improve the functionality of the entire assistance system (digital twin).

IV. Results

From the segmentation result relevant information for the tamping process is derived, e.g. exact ballast areas (into which the tamping tines can penetrate) but also sleeper positions and orientations, which are important for correct control of the tamping units. Additionally, the beginning and ending of turnout sections are identified automatically. Also, special equipment along the rail track (like switch rods, etc.) can be identified robustly (Fig.4).

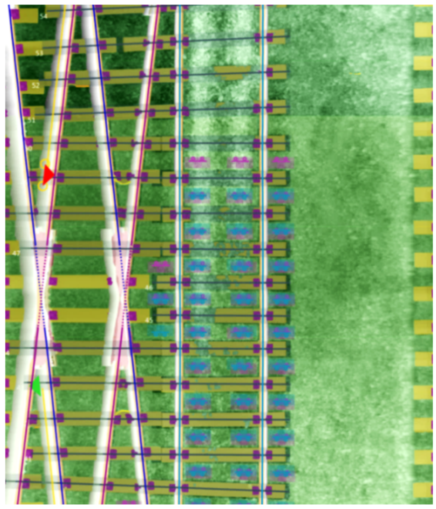

Fig. 4. Typical result of the segmentation process. Different segmented classes such as ballast (green), sleepers (yellow), tracks (white), screws (purple) and plants (green) are shown as a half transparent overlay on the depth image.

First tests in real operation confirm the excellent suitability of the method described. In conclusion, deep learning based semantic segmentation enables the practical realization of very robust outdoor applications under very harsh conditions. The algorithms used are constantly being improved - for example, a new generation of network architecture with an improved segmentation approach is currently being worked on which promises to further improve the detection properties even for very small or thin objects (such as cables, etc.).

Acknowledgement

We thank our colleagues from the department Digital Track Systems (Plasser & Theurer) for their support.

References

[1] Homepage Plasser & Theurer: https://www.plassertheurer.com/en/machines-systems/tamping.html

[2] F. Auer et al.: Smart Tamping Anwendungsmglichkeiten des Weichenstopf-Assistenzsystems, ZEVrail 2018, Nr. 6.

[3] M. Buerger et al.: Hilfe beim Stopfen Entwicklung eines Weichenstopf-Assistenzsystems, Eisenbahn-Ingenieur 2017, Nr. 6

[4] Jonathan Long et al.: Fully Convolutional Networks for Semantic Segmentation, 2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR); Electronic ISBN: 978-1-4673-6964-0