

# Using Technology Developed for Autonomous Cars to Help Navigate Blind People

Manuel Martinez   Alina Roitberg   Daniel Koester   Boris Schauerte   Rainer Stiefelhagen

Karlsruhe Institute of Technology  
Institute for Anthropomatics and Robotics  
76131 Karlsruhe, Germany  
<http://cvhci.anthropomatik.kit.edu/>

## Abstract

*Autonomous driving is currently a very active research area with virtually all automotive manufacturers competing to bring the first autonomous car to the market. This race leads to billions of dollars being invested in the development of novel sensors, processing platforms, and algorithms.*

*In this paper, we explore the synergies between the challenges in self-driving technology and development of navigation aids for blind people. We aim to leverage the recently emerged methods for self-driving cars, and use it to develop assistive technology for the visually impaired. In particular we focus on the task of perceiving the environment in real-time from cameras. First, we review current developments in embedded platforms for real-time computation as well as current algorithms for image processing, obstacle segmentation and classification. Then, as a proof-of-concept, we build an obstacle avoidance system for blind people that is based on a hardware platform used in the automotive industry. To perceive the environment, we adapt an implementation of the stixels algorithm, designed for self-driving cars. We discuss the challenges and modifications required for such an application domain transfer. Finally, to show its usability in practice, we conduct and evaluate a user study with six blindfolded people.*

## 1. Introduction

Humans rely strongly on vision, our primary sense used for perception of surroundings. Our daily life independence is closely connected to the ability to explore new environments and detect obstacles in a safe way. Navigation in an unknown setting is therefore a very difficult task for visually impaired people, often limiting their independence.

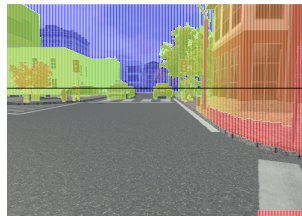
World Health Organization estimates around 285 million people worldwide to be visually impaired with around 39 millions being diagnosed with blindness [2]. Especially in



(a) Tartan Racing Car (2007)



(b) Google Autonomous Car (2015)



(c) Stixels for Autonomous Cars



(d) Stixels for Blind Assistance

Figure 1: High investment in autonomous cars promotes rapid development of new technologies, some of them can be transferred to assistive systems for the visually impaired. **1a:** Tartan Racing, winner of the 2007 DARPA Challenge. **1b:** 100% Autonomous car developed in 2014 by Google. **1c:** Stixels computed on GPUs for autonomous driving. [12] **1d:** Our proof-of-concept: Stixel-based obstacle detection re-applied to assist visually impaired people.

developed countries, the demand for assistive technologies for the blind grows due to the demographic shift towards an elderly population, the group most susceptible to low vision. Still, the market for vision-based navigation aids for the visually impaired remains small.

In contrast, strong interest in autonomous vehicles accelerated the progress in new technologies, creating a very active research field. Problem statements in this area are often related to computer vision, as understanding what is going on outside and handling uncertain situations even un-

der difficult weather conditions is crucial for traffic safety. This is very similar to the challenges visually impaired people face in their everyday life. The booming field of autonomous driving can therefore also lead to progress in the much smaller domain of assistive technologies for the blind. Bringing those applications together and discussing, how development of new aids for visually impaired people can benefit from much larger automotive industry, is the main topic of this work.

This paper is organized in two parts. First, we discuss the feasibility of transferring technologies extensively used for navigation in Advanced Driver Assistance Systems (ADAS) to assist visually impaired people in outdoor and indoor navigation. We overview the state-of-the-art ADAS technology, and highlight the potential areas that can be re-used to create assistive technology.

In the second part, we demonstrate the feasibility of such technology transfer in practice. We present a prototype obstacle avoidance system for blind people and test its effectiveness in a user-study. Technology from the automotive sector plays an important role in both software- and hardware design. We adapt the stixel-based obstacle detection method from the automotive industry as an aid for the navigation of the visually impaired people. The input of a wearable depth sensor is processed with an extended version of the stixel computation algorithm. An audio interface is warning the human of the detected obstacles and indicating both their distance and size. Our approach is mainly focused on mid-range obstacle detection, since we see the method as an addition to the classical white cane. Still, our method is able to detect near-range obstacles.

Our user study evaluation and benchmark of the presented system show that automotive-inspired technology can indeed be applied to aid the visually impaired.

## 2. Synergies between Autonomous Cars and Assitive Technology for the Blind

Autonomous driving technology has many facets, but in all cases, the car must perceive the environment using a set of sensors, then the information from the sensors must be processed to understand the environment using specialized algorithms, and, finally, a control system must decide about the most appropriate course of action in current situation.

This control loop (perception - understanding - action) must satisfy several properties: it must be executed in real-time, handle previously unseen environments, be robust under varying environmental conditions, and, last but not least, be safe for both, users and pedestrians around them.

We can see many similarities between the control loops of self-driving cars and navigation aids for the visually impaired. To help navigate visually impaired people we must also perceive the environment using a set of sensors and understand the environment using algorithms. However, in-



Figure 2: Lidars and cameras are the main sensors used to map the road ahead of the car. Left: Velodyne HDL-64E lidar, which costs *ca.* \$75,000. Right: Volvo's customized windshield camera array. Sources: Velodyne and Volvo.

stead of just controlling the car, navigation aids must communicate with the user to suggest a course of action or alert about an impending obstacle.

Although both tasks do not have identical goals, researchers of navigation aids for the blind can benefit of the impressive developments achieved in self-driving cars.

Here we present an overview of the current developments in sensors, algorithms and processing platforms that can be applied to navigational aids for the visually impaired.

### 2.1. Sensors

The main goal of sensors is to perceive the environment, and thus they are a critical part of the system: we simply cannot avoid obstacles that we can't sense.

There is no sensor modality that is capable, by itself, to perceive all possible challenges in all environments, therefore a self-driving car must combine sensors from multiple modalities. Ultrasound sensors are popular because they are robust and inexpensive, but their low range limits their usefulness to aid in parking and to act as a last option safety feature. On the other hand, radars, lidars and cameras are used for long range sensing. Radars do provide limited spatial information, so they are mainly used as a safety feature only, thus lidars and cameras are the two main modalities used to map the road (see Figure 2).

Lidars (a portmanteau of light and radar) are sensors that use laser range sensing technology to create a 3D map of the environment, in cars they are usually installed on the roof. Lidars were popular in the initial stages of research, and most of the participants on the Darpa Grand Challenge competitions that took place between 2004 and 2007 used them, but currently they have fallen out of favor. This is mainly due to two factors: first, lidars are expensive, with hardware costs in the range of tens of thousands of dollars, and second, the technology behind lidars is sensitive to environmental conditions and has trouble recognizing the environment in case of rain or snow [23]. Waymo (formerly a part of Google) still invests heavily in lidar technology, and has vowed to reduce hardware costs by 90% [3].

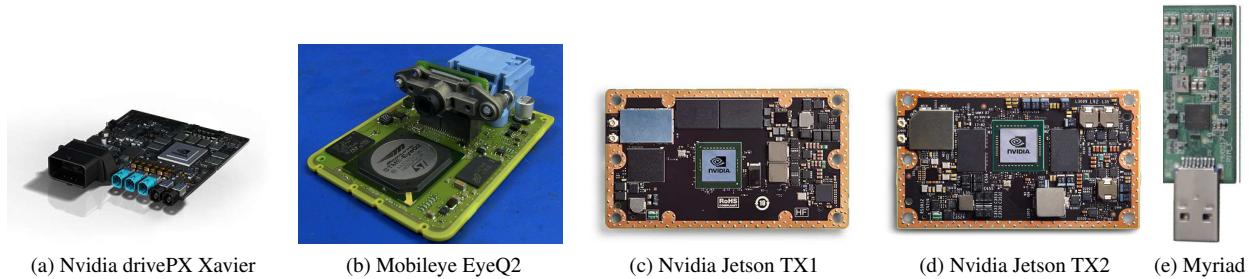


Figure 3: Overview of embedded platforms used in automotive industry. From left to right: Nvidia drivePX Xavier; the PCB and camera module from a Hyundai Lane Guidance, which is based on the EyeQ2 chip from Mobileye ; Nvidia Jetson TX1 (used in our proof-of-concept); Nvidia Jetson TX2, which is an upgrade over the TX1; Fathom inference engine in a USB stick form factor. It is powered by the Myriad 2 MA2450 chip. Sources: Nvidia, Binarysequence and Movidius.

Self-driving technology has migrated slowly but steadily towards using cameras as the main sensors for environment modeling and understanding. As of 2017, camera-based systems dominate the research being published in the field. Cameras are relatively inexpensive but processing images is significantly more complex than using lidars or radars, which provide 3D world models directly. The use of cameras as sensors for self-driving cars has become viable due to the recent advances in large scale machine learning, as well as the development of new hardware that is able to execute image processing algorithms in an embedded form factor.

There is high potential in integrating sensor modalities used for self-driving cars into navigational assistive systems for the visually impaired: ultrasound sensors [24], lidars [16] and cameras [7, 19].

## 2.2. Platforms

Image processing algorithms are very demanding in terms of processing power compared to almost any other modality. A Full-HD color camera contains approximately 2 megapixels and produces images at 60 frames per second, generating 360 million values per second, if the camera is HDR (High Dynamic Range), this translates into 720 Megabytes per second. This is a staggering amount of data to transfer and process in real-time and autonomous cars use many cameras to cover the whole 360° environment.

Most CPUs are not capable of processing this amount of data sequentially, and thus specific instruction sets were designed to process multiple pixels simultaneously, like the MMX (MultiMedia eXtensions) introduced in 1997 by Intel. Even using those instruction sets most CPUs struggle with image processing. This means that a very large amount of power must be used to process images, and this hinders its integration into a self-driving car (or a mobility aid for the blind).

The current trend is to leverage the fact that most image processing algorithms can be parallelized easily. By using GPUs (Graphical Processing Units), it is common to achieve a performance/power ratio around 10 times better than when using CPUs [20]. Nvidia, the lead GPU manufacturer, is offering a family of platforms named Drive PX that are designed specifically for self-driving cars, are compact, and use a small amount of power (see Figure 3a).

What is noteworthy, is that the same processors used in the Drive PX family are also made available in the form of compact modules named Jetson (see Figure 3c). This way the processors used in self-driving cars are made available also for the general use.

Still, Nvidia embedded platforms are relatively large and power hungry because they are the result of scaling down an architecture designed originally for desktop computers. Instead, several companies are building chips designed for scratch for embedded applications, we would like to highlight Mobileye and the EyeQ platform (see Figure 3b) as well as Movidius and the Myriad platform (see Figure 3e). Details about Mobileye solutions are scarce, but their EyeQ platforms seem to be designed exclusively for autonomous driving. On the other hand, Movidius technology is well known [14] and it has been tested in many applications. Both companies have been acquired recently by Intel, and thus at the moment it is still not clear if Intel will support the development of assistive technology for the visually impaired.

## 2.3. Algorithms

Many algorithms developed for self-driving cars can also be used as components for a navigation aid for the visually impaired. Both tasks present similar challenges for camera calibration, image processing, scene understanding, environment mapping, obstacle recognition, planning, localization and visual odometry, among others. A comprehensive review of the recent developments for all those challenges

falls out of the reach of this paper, instead, we would like to highlight projects that deliver publicly available code that can be easily adapted for its use in assistive navigation tools.

We start with a stereo matching implementation optimized for the Nvidia embedded platforms [11]. This work implements the popular Semi-Global Matching algorithm [13] and achieves 42 frames per second for an image size of  $640 \times 480$  on a Jetson TX1 module. This implementation allows us to obtain a depth field from the images, and thus a better spatial perception of the scene.

Using the depth information we can obtain a better representation of the environment by using stixels [4]. Stixels offer a mid-level representation of the scene where the image is divided in vertical regions that are segmented based on their disparity (see Figure 1c). Compared to other segmentation algorithms, stixels can be calculated very efficiently [12] and their representation is well suited to distinguish between obstacles and ground.

The next level of understanding is to find all semantically significant objects in the image. This task is commonly tackled by convolutional neural networks, but the best performing networks are usually not fast enough to be embedded in cars or mobile applications, therefore there are several attempts at speeding up the task either by using custom architectures [22] or even using stixels as a basis [18], as seen in Figure 4.

Mentioned techniques only provide image analysis with no actual decision taking, which is delegated to a future stage. Instead of splitting the perception and the control stages, Nvidia suggests that it might be more efficient to use an end-to-end network that generates control signals for the car based only on the source images, with no intermediate steps [5].

### 3. Proof of Concept: Obstacle Avoidance for the Visually Impaired based on Stixels

For a long time, navigation aides for the visually impaired have been limited to classical training-intensive tools, such as white canes or blind dogs [8], and both still remain the modality of choice for most of the visually impaired people due to their reliability and convenience.

White canes are excellent for detecting ground-level obstacles very close to the user, which is crucial for the safety. However, the user does not obtain much information about the orientation and the medium- or long-range environment topology, which is an important navigation cue. Therefore, there has been extensive work developing electronic aids to increase the sensing range [8, 19].

Often, progress in this area is connected to technological developments in other fields. For example, Kulyukin *et al.* uses Radio Frequency Identification (RFID) cues to navigate through novel environments [15]. Smartphone technology, which integrates cameras, powerful processors, and

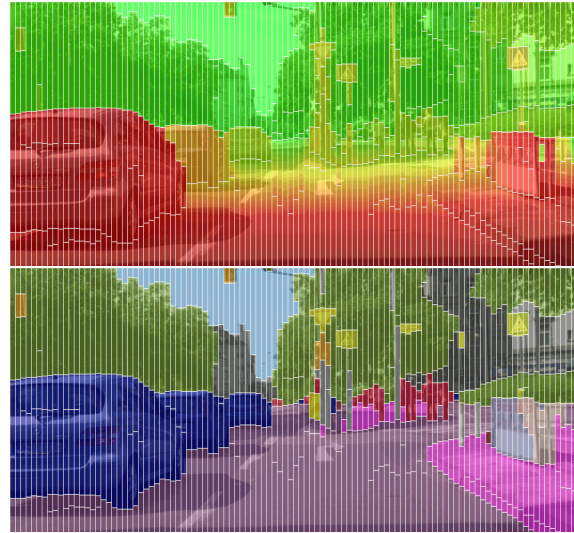


Figure 4: Top: stixels obtained from a driving scene. Bottom: their semantic segmentation. Source: Stixel-world [18].

GPS technology, is enabling many of the recently developed assistive technology, like the navigation app named VoiceMaps [9, 25], and the camera-based obstacle avoidance system by Tapu *et al.* [21].

To explore the potential of transfer driverless car technology to practical assistive tools for the blind, we adapt one of the prominent algorithms for depth-based obstacle detection from the automotive industry and for its use as an assistive tool for the visually impaired.

#### 3.1. System Setup

As a proof of concept, we built an obstacle avoidance system that must alert an user of an obstacle in their immediate proximity. As an input sensor we use an Asus Xtion Pro, which is a lightweight (225g) and low power depth camera that suits our environment well. The Xtion Pro provides disparity images at a resolution of  $640 \times 480$  pixels at 30 frames per second.

We process the disparity image using the stixels algorithm using the implementation suggested by Hernandez *et al.* [12], which was developed for automotive applications, and meant to be executed on a Nvidia GPU.

To compute the stixels, we use a Jetson TX1 development kit from Nvidia. The Jetson TX1 is powered by the Tegra T210 processor that features four 64-bit ARM cores and 256 CUDA cores [1].

We use bone conducting headphones to provide feedback to the user by generating beeps, whose sound and frequency are related to the size and distance of the objects detected by the stixel algorithm.

An overview of the system is shown in Figure 5.

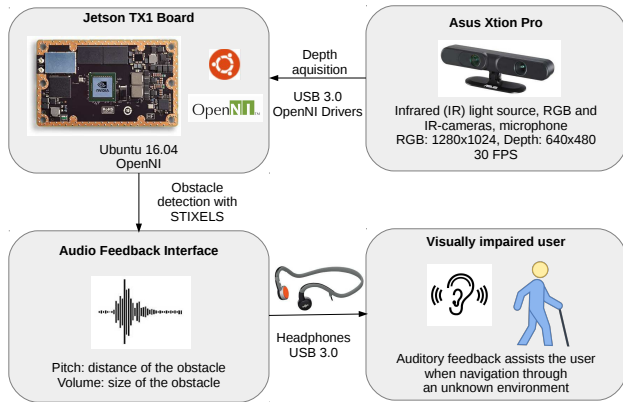


Figure 5: Overview of the developed system, inspired by automotive technology.

### 3.2. Source Algorithm

Our source algorithm is a fast implementation of the stixels segmentation approach designed to be run in real-time in embedded GPU platforms [12]. The stixels segmentation approach, which uses a single disparity image as a source, divides the field of view in a number of columns, which are divided into segments belonging to one of the following three classes: ground, obstacle, or sky. For each segment, the algorithm provides its class, the start position, its length, and its disparity value. The basic assumption of the algorithm is that the sections parallel to the ground belong to the ground itself, while obstacles are mainly vertical with respect to the ground. Although this view is an oversimplification of the real world, it has shown to be successful at detecting obstacles and is computationally efficient.

The source code of this approach has been made publicly available, and it is optimized for the Jetson TX1 platform, where it achieves 45.7 frames per second when using a resolution of  $640 \times 480$ . For details of the algorithm and its implementation we refer to the original publication in [12].

#### 3.2.1 Ground Plane Estimation

From the programming point of view, the stixel classification algorithm has two main steps: first, the height and pitch of the camera with respect to the ground is estimated, and second, the disparity image is segmented in stixels.

Our test implementation assumes that the camera is fixed to the car, and thus the pitch and roll of the camera are zero in all cases. In our application, the roll was not zero because the camera was placed in the chest of a person, but the algorithm is robust enough to deal with those cases.

The main problem we faced is that the original algorithm uses a Hough-based line detector [6] to localize the vanish-

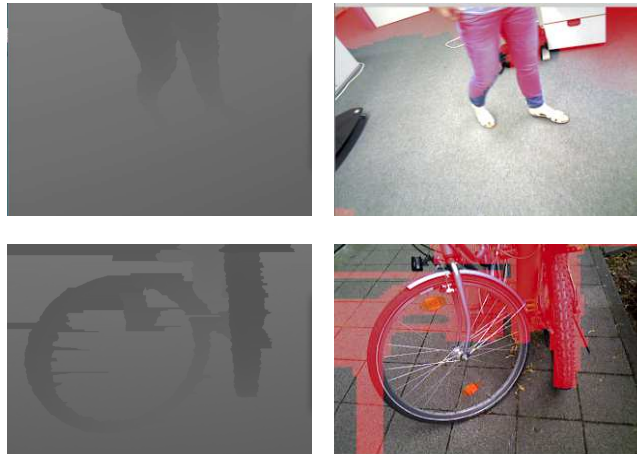


Figure 6: Raw depth output from Asus Xtion Pro sensor (left) and output of the stixel based obstacle detection system (right). Red markings indicate the detected obstacles.

ing point of the image, and uses the geometrical properties between the detected lines and the vanishing point to estimate the horizon line, and the camera height and pitch. This approach works well in cars (see Figure 1c), but it isn't as successful in human environments.

Instead, we implemented our own ground plane estimation. We divide the source disparity image in blocks of  $4 \times 4$  pixels. To speed up our algorithm, we select randomly 10% of the blocks in the lower half of the field of view (closer to the user), and calculate the direction of the normal vector per block. Then we cluster the normal vectors using Expectation-Maximization and find the main component, which we assume corresponds to the normal of the ground. We found this algorithm to be fast and robust, and it enables us to use the GPU accelerated stixel classification code.

Finally, we combined the ground plane estimation and the stixel algorithm to find obstacles from depth images, as seen in Figure 6.

#### 3.2.2 Obstacle Sonification

There are multiple ways to provide feedback information about the perceived obstacles to the user of the system [17]. In this proof of concept, for simplicity, we choose to use auditory feedback. As a transceiver, we use bone conducting headphones as they do not obstruct the ears, and allow the users to hear their environment.

Based on our previous experience, we choose to sonify only the obstacles right in front of the user, in order to minimize confusion and reduce cognitive load.

For each processed frame, we produce a tone for each of the stixels classified as obstacles that lie in the  $15^\circ$  frontal



Figure 7: Visualization of our the obstacle detection system algorithm developed for autonomous cars. Stixels-based method was adapted for assisting visually impaired people and tested in indoor and outdoor environments. Detected obstacles are marked in red. Top row: indoors. Bottom row: outdoors.

field of view of the user. The volume of each tone corresponds to the size of the stixel, thus a stixel that covers the whole height of the image would produce the loudest tone, whereas a stixel that only covers a single vertical pixel produces a tone that is only 1/480 of the same volume.

The frequency of the tones generated scales with the disparity of the stixel. Generally higher frequencies are associated to more urgent messages, so we set the frequency of the tone as 10 times the reported disparity. For the Asus Xtion, whose focal length ( $f$ ) is 575 and its baseline ( $b$ ) is 7.5cm, the formula for the disparity ( $d$ ) from the depth ( $z$ ) is as follows:

$$d = \frac{b \cdot f}{z} . \quad (1)$$

Therefore, an obstacle placed at one meter would generate a tone of 431 Hz, while the same obstacle placed at four meters generates a tone of 108 Hz.

### 3.3. Performance Evaluation

We measured the computational performance of the Jetson TX1 platform as well as its power usage when running the stixels code. As a baseline, we also measure the same algorithm running in a notebook equipped with a Core i7 5500U CPU and a GT840M GPU.

To measure the performance, we processed 500 disparity images, and we report the average processing time as well as the standard deviation (see Table 1). We measured independently the ground estimation part of the algorithm, which runs on the CPU, and the stixel calculation, which runs on the GPU. The notebook is 5.6 times faster for the ground plane estimation, and 4.0 times faster for the stixels calculation, and more importantly, the standard deviation is

more than 15 times lower on the notebook than on the Jetson TX1.

	Jetson TX1	i7 5500U + GT840M
Ground	41.1(±8.2)ms	7.28(±0.46)ms
Stixels	35.2(±13.9)ms	8.70(±0.60)ms

Table 1: Performance evaluation of our ground plane estimation algorithm and the stixels algorithm in the Jetson TX1 platform, compared to a notebook. Standard deviation in brackets.

Regarding power usage, we monitored the systems idle, streaming from the depth camera (without performing any processing), and running the stixels code (see Table 2). In both cases the WiFi signal was enabled, and the notebook screen had its brightness set to its minimum level. We would highlight that the Jetson TX1 consumes almost 4 times less power than the notebook when idle, and almost 3 times less than the notebook when processing stixels.

The numbers we provide include the power consumed by the Asus Xtion Pro depth camera, incidentally proving that this depth camera is significantly more power friendly than the Kinect v2, which uses 16 Watts.

This results show that, although the embedded platform is significantly less powerful than a common notebook, it provides sufficient performance for the task (allowing more than 10 frames per second) while consuming little power.

For our use case, the Jetson TX1 was powered by a compact and portable 75 Watt-hour battery, thus the endurance of the system as we tested it was around 9 hours.

	Jetson TX1	i7 5500U + GT840M
Idle	3.1W	12.1W
Streaming	6.1W	13.2W
Stixels	8.3W	22.5W

Table 2: Power consumption evaluation of the Jetson TX1 platform, compared to a notebook. Standard deviation is in brackets.

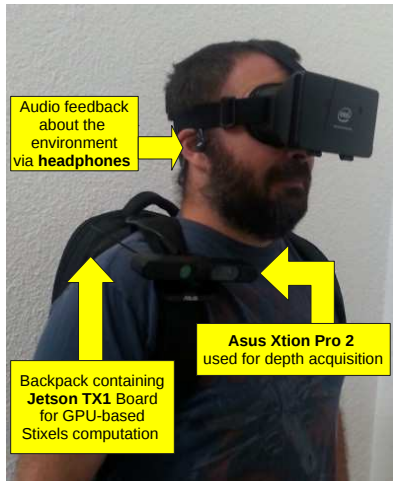


Figure 8: Blindfolded user equipped with the developed prototype system. Computing board is placed inside the backpack and Asus Xtion Pro sensor is attached to its strap in the front. Sound helps the user to avoid detected obstacles.

### 3.4. Conducted User Study

The conducted experiment has two main objectives. First, we research the potential of driverless car technology for assisting impaired vision in health care in general. To do so, we implement a prototype for a novel assistive navigation system for the blind, using algorithms of driver less car technology and test general feasibility for obstacle detection. Secondly, we objectively evaluate current stage of the prototype development in a user study.

The study was conducted with six probands (N=6, two female, four male). At this stage of development, we have invited participants without visual impairment, who were artificially blindfolded with a mask.

At the beginning, the subject set on the mask and was equipped with the backpack containing the computing board. The Asus Xtion Pro Sensor was located on the backpack strap approximately at the height of subjects shoulder, as shown in Figure 8. The subject received instructions about the audio interface and was given a few minutes to get used to the situation and try out the system with different obstacles.

Mean NASA-TLX Evaluation Score by Category



Figure 9: Results of the NASA-TLX assessment test. The finger displays average scores (scale from 1 to 100) reported by the subject after the obstacle avoidance experiment.

Subject's task in the experiment was to walk through a long corridor from the beginning to the end with multiple obstacles, blindfolded, using only the auditory interface of the system. Every-day obstacles, which are indeed a challenge for blind people, such as chairs or a ventilator, were placed in the corridor. The placement was re-arranged after the subject put on the mask, so that he or she was unaware of the surrounding obstacles. It should be mentioned, that the walls and open doors in the corridor are also problematic, as a blindfolded person easily becomes disoriented and even going through an obstacle-free corridor in a straight line is not easy. The system assists the user in going in a straight line by emitting louder signal when the sensors angle shifts towards one of the walls. Examples of the algorithm output in the experiment scenario are shown in Figure 7.

Figure 7 also shows multiple outdoor examples of the obstacle detector output, where bicycles, cars, bushes and pedestrians are successfully identified as an obstacle. Outdoor tests were, however, only Proof-Of-Concept experiments and did not include a quantitative user study yet.

After the task is completed, the user is asked to evaluate the system by answering standardized NASA TLX form [10] questions, giving valuable feedback for further development. The user rates the perceived workload of the task in six subscales: *Mental Demands*, *Physical Demands*, *Temporal Demands*, *Own Performance*, *Effort* and *Frustration*.

Individual assessments of the participants were averaged, the results are shown in Figure 9. Low scale in NASA-TLX test corresponds to low reported levels of the corresponding aspect (e.g. *Mental Demand*). An exception is the evaluation of *Performance*, where low value corresponds to successful performance and the value of 100 is the lowest level of performance possible. Lower values on

each of the scales therefore indicate higher effectiveness of the system. *Mental Demand*, *Effort* as well as *Temporal Demand* were very close to a medium value on the scale. Values slightly higher than medium were observed as it comes to *Frustration* and slightly lower values as it comes to *Performance* (as mentioned before, low values indicate high performance at the scale).

Significantly lower rating was reported in regard to *Physical Demand*. This is, on the one hand, not surprising, since the navigation is rather mentally, not physically, challenging. On the other hand, good values in Physical Demand indicate that the system, where the depth sensor and the computing board are being carried by the person, is not intrusive or too heavy.

One should take into account that the study was conducted on people with normal vision, who were artificially blindfolded. The probands are therefore not used to the setting of absent vision and high levels of frustration might also be connected with the fact that exploring an environment without vision is, in general, a very hard task. In the future it is therefore crucial to conduct a large-scale study on visually impaired people, who are familiar with this challenges. However, the experiment evaluation has shown, that applying algorithms used for driverless car navigation for human navigation, is, indeed, possible. The user study delivered very valuable feedback, which will help us in further development stages.

## 4. Conclusion and Discussion

In this work we discussed the technical feasibility of transferring technology developed for autonomous cars into assistive technology for blind and visually impaired people.

We present an overview of the current developments in autonomous industry, covering, in particular, the sensors, platforms, and algorithms that are used to perceive and analyze the surrounding environment of the car. We highlight the synergy that exists between both fields, and note how some of the developments made for cars can be used for assistive purposes. As a proof of concept, we have built an obstacle avoidance system based on an object detection algorithm designed for cars. Due to the small differences in both settings (*i.e.*, camera position, and the surrounding environment), we had to slightly adapt the preprocessing step of the algorithm. Otherwise, the algorithm was successfully used to detect obstacles in both indoor and outdoor environments, which was evaluated in a user study.

A large amount of capital is currently being invested in new technology for autonomous driving, accelerating research progress in this field. We expect that such results can be highly beneficial in the research of assistive tools to help navigate blind and visually impaired people, and improve their quality of life. This work is a proof of concept that the research transfer in such a direction is possible.

## Acknowledgements

This work has been partially funded by the German Federal Ministry of Education and Research (BMBF) under grant no. 16SV7609 within the TERRAIN project.

## References

- [1] NVIDIA Jetson embedded systems developer kits, modules, sdks. <http://www.nvidia.com/object/embedded-systems-dev-kits-modules.html>. Accessed: 2017-06-30. 4
- [2] World Health Organization visual impairment and blindness. <http://www.who.int/mediacentre/factsheets/fs282/en/>. Accessed: 2017-06-30. 1
- [3] J. Ayre. Waymo shaved 90% off lidar sensor cost. <http://goo.gl/BfC6Rw>. January 9th, 2017. 2
- [4] H. Badino, U. Franke, and D. Pfeiffer. The stixel world-a compact medium level representation of the 3d-world. In *DAGM-Symposium*. Springer, 2009. 4
- [5] M. Bojarski, D. Del Testa, D. Dworakowski, B. Firner, B. Flepp, P. Goyal, L. D. Jackel, M. Monfort, U. Muller, J. Zhang, et al. End to end learning for self-driving cars. *arXiv preprint arXiv:1604.07316*, 2016. 4
- [6] R. O. Duda and P. E. Hart. Use of the hough transformation to detect lines and curves in pictures. *Communications of the ACM*, 15(1):11–15, 1972. 5
- [7] H. Fernandes, P. Costa, V. Filipe, L. Hadjileontiadis, and J. Barroso. Stereo vision in blind navigation assistance. In *World Automation Congress (WAC)*. IEEE, 2010. 3
- [8] N. A. Giudice and G. E. Legge. Blind navigation and the role of technology. *The Engineering Handbook of Smart Technology for Aging, Disability, and Independence*, 2008. 4
- [9] L. Hakobyan, J. Lumsden, D. OSullivan, and H. Bartlett. Mobile assistive technologies for the visually impaired. *Survey of ophthalmology*, 58(6):513–528, 2013. 4
- [10] S. G. Hart and L. E. Staveland. Development of nasa-tlx (task load index): Results of empirical and theoretical research. *Advances in psychology*, 52:139–183, 1988. 7
- [11] D. Hernandez-Juarez, A. Chacón, A. Espinosa, D. Vázquez, J. C. Moure, and A. M. López. Embedded real-time stereo estimation via semi-global matching on the gpu. *Procedia Computer Science*, 80:143–153, 2016. 4
- [12] D. Hernandez-Juarez, A. Espinosa, J. C. Moure, D. Vázquez, and A. M. López. Gpu-accelerated real-time stixel computation. In *Winter Conference Applications of Computer Vision*, pages 1054–1062. IEEE, 2017. 1, 4, 5
- [13] H. Hirschmuller. Stereo processing by semiglobal matching and mutual information. *IEEE Transactions on pattern analysis and machine intelligence*, pages 328–341, 2008. 4
- [14] M. H. Ionica and D. Gregg. The movidius myriad architecture’s potential for scientific computing. *IEEE Micro*, 35(1):6–14, 2015. 3
- [15] V. Kulyukin, C. Gharpure, J. Nicholson, and S. Pavithran. Rfid in robot-assisted indoor navigation for the visually impaired. In *Intelligent Robots and Systems (IROS)*, volume 2. IEEE, 2004. 4

- [16] T.-S. Leung and G. Medioni. Visual navigation aid for the blind in dynamic environments. In *Computer Vision and Pattern Recognition Workshops*, pages 565–572, 2014. 3
- [17] M. Martinez, A. Constantinescu, B. Schauerte, D. Koester, and R. Stiefelhagen. Cognitive evaluation of haptic and audio feedback in short range navigation tasks. In *Proc. 14th Int. Conf. Computers Helping People with Special Needs (ICCHP)*, 2014. 5
- [18] L. Schneider, M. Cordts, T. Rehfeld, D. Pfeiffer, M. Enzweiler, U. Franke, M. Pollefeys, and S. Roth. Semantic stixels: Depth is not enough. In *Intelligent Vehicles Symposium (IV)*, pages 110–117. IEEE, 2016. 4
- [19] T. Schwarze, M. Lauer, M. Schwaab, M. Romanovas, S. Bohm, and T. Jurgensohn. An intuitive mobility aid for visually impaired people based on stereo vision. In *Proceedings of the IEEE International Conference on Computer Vision Workshops*, 2015. 3, 4
- [20] S. Shi, Q. Wang, P. Xu, and X. Chu. Benchmarking state-of-the-art deep learning software tools. *arXiv preprint arXiv:1608.07249*, 2016. 3
- [21] R. Tapu, B. Mocanu, A. Bursuc, and T. Zaharia. A smartphone-based obstacle detection and classification system for assisting visually impaired people. In *Proceedings of the IEEE International Conference on Computer Vision Workshops*, pages 444–451, 2013. 4
- [22] M. Trembl, J. Arjona-Medina, T. Unterthiner, R. Durgesh, F. Friedmann, P. Schuberth, A. Mayr, M. Heusel, M. Hofmarcher, M. Widrich, et al. Speeding up semantic segmentation for autonomous driving. *NIPSW*, 1(7):8, 2016. 4
- [23] Y. Wang, F. Fu, J. Shi, W. Xu, and J. Wang. Efficient moving objects detection by lidar for rain removal. In *International Conference on Intelligent Computing*, 2016. 2
- [24] D. Whittington, D. Waters, and B. Hoyle. The ultra cane. <http://www.ultracane.com>. June, 2011. 3
- [25] K. Yelamarthi, D. Haas, D. Nielsen, and S. Mothersell. Rfid and gps integrated navigation system for the visually impaired. In *Circuits and Systems*. IEEE, 2010. 4