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Obstacle detection using stereo imaging to assist the navigation of visually impaired people

Paulo Costa[a,]*, Hugo Fernandes[b], Paulo Martins[c], João Barroso[d], Leontios J. Hadjileontiadis[e]

[a] *School of Technology and Management, Polytechnic Institute of Leiria, 2411-901 Leiria, Portugal*
[b] *University of Trás-os-Montes e Alto Douro, 5001-801 Vila Real, Portugal*
[c] *INESC TEC (formerly INESC Porto) / UTAD – University of Trás-os-Montes e Alto Douro, 5001-801 Vila Real, Portugal*
[d] *GECAD/UTAD – Knowledge Engineering and Decision Support Research Center, Vila Real, Portugal*
[e] *Department of Electrical and a Computer Engineering, Division of Telecomunications, Aristotle University of Thessaloniki, Thessaloniki, Greece*

Abstract

Assistive technology enables people to achieve independence when performing daily tasks and it enhances their overall quality of life. Visual information is the basis for most navigational tasks, so visually impaired individuals are at disadvantage due to the lack of sufficient information about their surrounding environment. With recent advances in inclusive technology it is possible to extend the support given to people with visual disabilities in terms of their mobility. In this context we propose and describe the Blavigator project, whose global objective is to assist visually impaired people in their navigation on indoor and outdoor environments. This paper is focused mainly on the Computer Vision module of the Blavigator prototype. We propose an object collision detection algorithm based on disparity images. The proposed algorithm uses a 2D Ensemble Empirical Mode Decomposition image optimization algorithm and a two layer disparity image segmentation to detect nearby objects.

Keywords: Assistive technologies; Obstacle detection; Stereo vision; Empirical Mode Decomposition.

* Corresponding author. Tel.: +351244820300; fax: +351244820310.
E-mail address: paulo.costa@ipleiria.pt

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1. Introduction

Assistive technology enables people with disabilities to accomplish daily tasks and assists them in communication, education, work and recreational activities. In general, it helps them to achieve greater independence and enhance their overall quality of life. From the different assistive technologies available, a special focus was put on those that enhance the mobility of blind or visually impaired people.

The World Health Organization estimates that 285 million people are visually impaired worldwide: 39 million are blind and 246 have low vision [1]. Blind or visually impaired people have a considerable disadvantage as they lack information for bypassing obstacles and have relatively little information about landmarks, heading, and self-velocity. The main objective when designing this kind of assistive technology is to provide useful additional information to blind people during their mobility process, i.e. walking.

Human mobility comprises orientation and navigation. Orientation can be thought of as knowledge of the basic spatial relationship between objects in the environment. Information about position, direction, desired location, route, route planning etc, are all bound up with the concept of orientation. Navigation, in contrast, suggests an ability to move within the local environment. Navigation implies the knowledge of immediate objects and obstacles, features present on the floor (holes, stairs, flooring etc.), and of dangers coming from moving and/or stationary objects.

The present work proposes an object collision detection algorithm to be used in the computer vision (CV) module that will be integrated with the Blavigator prototype, described later in this paper. The new algorithm works in conjunction with previously developed algorithms [2] to provide secure navigation along a predefined route, in the presence of obstacles. Using a pre-calibrated stereo imaging system from Point Grey Research [3] the computer vision module obtains disparity images and calculates the depth information required to perform layer image segmentation. The images are segmented at predefined distances to find obstacles nearby and to inform the user on how to avoid the detected objects. The algorithm we propose uses Ensemble Empirical mode decomposition (EEMD) to optimize the disparity image and a two layer image segmentation algorithm to find objects.

The paper is organized as follows. Section II presents a classification of recent navigation systems to assist visually impaired people. Some projects that represent the state of the art are presented. Section III explains the proposed algorithm and the related techniques used. Section IV presents and discusses some results obtained. Finally, Section V concludes the paper with some final remarks.

2. Navigation system to assist visually impaired people

An Electronic Travel Assistant (ETA) has to supply the visually impaired with the necessary routing information to overcome obstacles in the near environment, with minimum errors. A distinction must be made between primary support systems such as the guide cane and the guide dog, and the secondary support systems, which use the most recent technologies.

These secondary support systems are the focus of the current study and typically consist of a wearable or handheld computer with Global Positioning System (GPS) responsible for macro navigation. In order to prevent collision with obstacles (micro navigation) these secondary systems also make use of the services provided by primary support systems. In the mid nineties, Collins and Loomis independently proposed the use of GPS to assist navigation for the visually impaired, in their navigation systems [4].

According to the model proposed by Loomis [4] a system to assist navigation for visually impaired people is composed by three main basic components: 1) the position and orientation unit is responsible for supplying the navigation system with the user’s location in the form of local and/or global coordinates. Due to the strong dependence on the environment in which the system is being used, this is the functional block that more strongly characterizes the navigation system; 2) the Geographic Information System (GIS) contains georeferenced data, stored in a database. This functional block is an essential component of the navigation system. Its main function is to store additional information about user's possible position, maps, object locations and possible dangers; 3) the user interface is the most critical component in the navigation system for assisting the visually impaired because it acts as a substitute for natural vision sensing (or so attempts to). The user interface must be user-friendly never reveal to be an 'obstacle' itself. Typically, interaction with the visually impaired user is made through audio interfaces, like Text-To-Speech (TTS) or virtual audio (sonification) and tactile displays like Braille keyboards or vibrotactile devices.

2.1. Navigation systems and related work

Navigation systems designed to assist visually impaired people can be classified in three main groups, based on their usage. Indoor systems are to be used in structured environments with less complex scenes, typically inside buildings or in controlled environments. Outdoor navigation systems are intended to be used in outdoor open space, typically on the street. Indoor/outdoor systems can be used in both indoor and outdoor environments, switching functionalities based on the surrounding environment.

Following paragraphs present some commercial and research (R&D) projects that currently describe the state of the art in outdoor navigation systems for assisting visually impaired people.

1) Navigation systems without local obstacle information, like BrailleNote GPS [5], StreetTalk [6], Trekker [7], NOPPA [8], Navigator [9] and Drishti [10] are GPS based systems to assist the navigation of visually impaired people. Their primary components are a PDA or Laptop specifically designed/adapted for people with visual disabilities, a Bluetooth GPS receiver and specially developed software for orientation, route mapping and configuration. User interaction can be made with a Braille display or a speech synthesizer.

2) Navigation systems with local obstacle information provide better knowledge of the local scenario, increasing the amount and the quality of the information provided to the blind user, which is very helpful to overcome local obstacles.

Several techniques can be used to detect and retrieve information about the environment like multiple ultrasonic sensors (sonar) [11], Laser Range Scanner (LRS) [12] and computer vision (CV) techniques [13], [14], [15], [16] and [17].

2.2. Blavigator system

A system to assist the navigation of blind or visually impaired people is currently being developed at the University of Trás-os-Montes and Alto Douro (UTAD). This project is named Blavigator, which is the successor of the previously developed SmartVision project [2], and its main objective is to develop a cheap and easy to use mobile navigation system that helps visually impaired people to navigate, providing ways to get to a desired location and, while doing so, providing contextual information about obstacles and points-of-interest (POI) like zebra-crossings, building entrances, etc. The system is built in a modular structure, combining several technologies, as seen in Fig. 1.

The Decision Module is responsible for managing and establishing communication between all the available modules. This module also receives inputs from the user and makes decisions on what information the user should get from the system. The Location Module is responsible for providing regular updates on the user's current geographic coordinates to the Decision Module. To provide this information both in indoor and outdoor environments, this module uses different technologies: Global Positioning System (GPS) for outdoor environments and Wi-Fi for indoor environments.

Radio-Frequency Identification (RFID) and Computer Vision are used in both indoor and outdoor environments and they are based on the detection of landmarks placed in the ground.

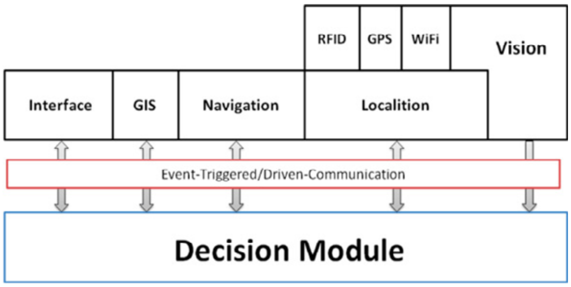

Fig. 1. Blavigator modular structure

Each location technology has a specific accuracy and the Location Module always chooses the one with the best accuracy from the ones available in each moment. In terms of hardware, the RFID reader is placed in the white cane (connected via Bluetooth) and the camera is chest-mounted. The GPS antenna and Wi-Fi antenna are built-in components of the mobile computer.

The Navigation Module is responsible for route planning and for providing information about surrounding points-of-interest (POI). It communicates with the Decision Module and requests two different data inputs: GIS data and location data. To get the GIS data, the Decision Module queries the GIS server in order to get maps and POIs. The user location is fed from the Location Module. After analyzing the requested data, the Navigation Module feeds back the Decision Module with navigation instructions. The amount and accuracy of the GIS data stored in the GIS server is critical in order to feed the blind user with the most appropriate and accurate instructions.

The Computer Vision Module provides orientation instructions by detecting known landmarks in the ground and keeping the user within safe routes. Using a stereo vision system, disparity information is extracted from the captured image frames and can be used to create a depth map. This information is useful to know the distance between the user and detected landmarks. So, in addition to giving orientation instructions to the Decision Module, with distance information the Computer Vision Module has the ability to feed the Location Module with location information.

Finally, the Interface Module provides user interface using two outputs and one input. The two outputs are text-to-speech software and vibration actuators. Since the hearing sense is very important to blind users, the vibration actuators are used for navigation instructions and the voice interface is used for menu interaction and to provide POI information. The user gives inputs to the system by using a small four-button device to scroll between the menus, apply changes and go back to previous menus.

The user interacts directly with the Decision Module through the Interface Module and all the other modules are independent. This way, the user can get the required information even when some modules are not available, or cannot provide accurate information. For example, if GPS is not available or if the user is in an indoor environment, the Location Module can get information from the RFID tags, Wi-Fi or Computer Vision modules. Redundancy is, therefore, a very important factor to increase the overall reliability and accuracy of the system.

2.3. Computer Vision Module

Several image processing techniques are used to extract useful information from the scene, i.e., object identification and scene description.

Fig. 2. Bumblebee2 stereo system [3]

In the context of assisting visually impaired people, the computer vision model must deal with large amounts of image data (high bandwidth process) and provide useful information to the user (Human Computer Interaction - HCI) which is typically a low bandwidth process.

Several computer vision techniques have been used in navigation systems to assist people with visual disabilities. The Principal Component Analysis (PCA) was used in ASMONC [11]; the Tyflos system [12] uses Fuzzy Like Reasoning Segmentation; Expectation-Maximization (EM) algorithm was used by Zelek [14]; stereo vision for measuring distance from objects was used by Meers [16] and Hadjileontiadis [17]; a Neural Networks were used in NAVI [18], and later the same authors also tested Fuzzy Learning Vector Quantification (FLVQ) to classify objects in the scene.

The computer vision module of the Blavigator prototype is one of the most critical because it deals with large and heterogeneous amounts of data and, in general, requires higher computing power. All the computations in this work are made on a laptop computer and image acquisition is made using Bumblebee 2, developed by Point Grey Research [3]. The main objective is to adapt this work on a cheap and easy to use prototype (not necessarily a laptop).

The Bumblebee is a packaged system that includes two pre-calibrated digital progressive scan Sony ICX084 CCD cameras with a baseline (the distance between cameras) of 12cm, and a C/C++ Software Development Kit [3], and a 400 Mbps IEEE-1394 Firewire interface for high speed communication of the digital video signal. Gain and shutter control can be set to automatic or be adjusted manually. The calibration information is preloaded into the camera allowing the computer software to retrieve it for XYZ coordinate calculations and image correction.

The FlyCapture SDK was used for image capture and camera control. The image size used in this work is 512 by 384 pixels.

For the calculation of the disparity and the correction of the images we used the Triclops SDK that is provided together with the Bumblebee 2 stereo vision system. Figure 2 shows the Bumblebee 2 stereo camera.

3. Empirical Mode Decomposition

In the real world, data from natural phenomena like life science, social and economic systems are mostly non-linear and non-stationary. Fourier and wavelet transform (built upon predefined basis functions) are traditional methods that sometimes have difficulty in reveal the nature of complex real life data. The adoption of adaptive base functions introduced by Huang et al. [19] provided the means for creating intrinsic a posteriori base functions with meaningful instantaneous frequency in the form of Hilbert spectrum expansion [19]. This approach is embedded into a decomposition algorithm, namely Empirical Mode Decomposition (EMD) [19], which provides a powerful tool for adaptive multi-scale analysis of non-linear and non-stationary signals. EMD is a method of breaking down the signal without leaving the time domain. It filters out functions which form a complete and nearly orthogonal basis for the signal being analysed. These functions, known as Intrinsic Mode Functions (IMFs), are sufficient to describe the signal, even though they are not necessarily orthogonal [19]. IMFs computed via an iterative 'sifting process' (SP), are functions with zero local mean [19], having symmetric upper and lower envelopes. The SP depends both on an interpolation method and on a stop criteria that ends the procedure. Some updates to the 1D-EMD have been proposed which address mode mixing effects that sometimes occur in the EMD domain. In this sense, 1D-Ensemble EMD (1D-EEMD) has been proposed [20], where the objective is to obtain a mean ensemble of IMFs with mixed mode cancelation due to input signal noise addition.

3.1. 1D-Empirical Mode Decomposition (1D-EMD)

1D-EMD considers a signal $x(t)$ at the scale of its local oscillations [19]. Locally, under the EMD concept, the signal $x(t)$ is assumed as the sum of fast oscillations superimposed to slow oscillations. On each decomposition step of the EMD, the upper and lower envelopes are initially unknown; thus, an interactive sifting process is applied for their approximation in order to obtain the IMFs and the residue. The 1D-EMD scheme is implemented according to the following steps [19]:

1) Identify the successive extrema of $x(t)$ based on sign alterations across the derivative of $x(t)$;

2) Extract the upper and lower envelopes by interpolation; the local maxima (and minima) are connected by a cubic spline interpolation to produce the upper (and lower) envelope. These envelopes should cover all the data;

3) Compute the average of upper and lower envelopes, $m_1(t)$;

4) Calculate the first component $h_1(t) = x(t) - m_1(t)$;

5) Ideally, $h_1(t)$ should be an IMF. In reality, however, overshoots and undershoots are common, which also generates new extrema or exaggerate the existing ones [19]. To correct this, the sifting process has to be repeated as many times as it is required to reduce the extracted signal as an IMF. To this end, treat $h_1(t)$ as a new set of data, and repeat steps 1 through 4 up to k times (e.g., $k = 7$) until $h_{1k}(t)$ becomes a true IMF. Then set $c_1(t) = h_{1k}(t)$. Overall, $c_1(t)$ should contain the finest scale or the shortest period component of the signal;

6) Obtain the residue $r_1(t) = x(t) - c_1(t)$;

7) Treat $r_1(t)$ as a new set of data and repeat steps 1 through 6 up to N times until the residue $r_N(t)$ becomes constant, a monotonic function, or a function with only one cycle from which no more IMFs can be extracted. Note that even for data with zero mean, $r_N(t)$ can still differ from zero;

8) Finally,

$$x(t) = \sum_{i=1}^{N} c_i(t) + r_N(t), \qquad (1)$$

where $c_i(t)$ is the i-th IMF and $r_N(t)$ the final residue.

3.2. 1D-Ensemble Empirical Mode Decomposition (1D-EEMD)

One of the major drawbacks of the original 1D-EMD approach is the appearance of mode mixing, which is defined as a single IMF consisting of signals of widely disparate scales, or a signal of similar scale residing in different IMF components. Adding white noise scales uniformly through the whole time-scale or time-frequency space, which provides a reference distribution that facilitates the decomposition. The white noise added may also help extracting the true signals in the data, a truly Noise-Assisted Data Analysis [20]. The 1D-EEMD is implemented as follows:

1) Add white noise series w(t) to the data x(t), X(t) = x(t) + w(t);

2) Decompose X(t) data (with added white noise) into IMFs, $X(t) = \sum_{j=1}^{N} c_j(t) + r_N(t);$

3) Repeat step 1 and step 2 several times with different noise series wi(t), Xi(t) = x(t) + wi(t), and obtain corresponding IMFs, $X_i(t) = \sum_{j=1}^{N} c_{ij}(t) + r_{iN}(t);$

4) Finally, the ensemble mean of the corresponding IMFs that result from the decomposition are

$$c_j(t) = \frac{1}{N}\sum_{i=1}^{N} c_{ij}(t), \qquad (2)$$

where N is the number of ensemble members.

3.3. 2D-Empirical Mode Decomposition (2D-EMD)

The sifting notion is essentially identical in 1D and 2D cases. Nevertheless, due to the nature of the 2D data of the images, some issues should be handled with care.

In particular, in 1D space the number of local extrema and zero crossings of an IMF must be the same, or differ by one [19]. In a 2D space, the IMFs typically use the definition of symmetry of upper and lower envelopes related to local mean [21]. There are many ways of defining the extrema in use; hence, different local extrema detection algorithms could be applied. Fast algorithms use the comparison of candidate extrema with its nearest 8-connected neighbours [22], while more sophisticated methods, like morphological reconstruction, are based on geodesic operators [23]. Furthermore, the interpolation method should rely on proper 2D spline interpolation of the scattered extrema points. In [21] the thin-plate smoothing spline interpolation is used. In Bi-dimensional Empirical Mode Decomposition (BEMD) [23] Radial Basis Functions are used for surface interpolation. This combination of 2D extrema extraction and 2D surface interpolation requires very heavy computational power, suitable neither for real-time implementations nor for use in mobile devices.

3.4. Proposed computer vision approach

A disparity image or depth map is an efficient method for storing the depth of each pixel in an image. Each pixel in the depth map corresponds to the same pixel in an image, but the grey level corresponds to the depth at that point rather than the gray-shade or color.


a) b)

Fig. 3. Bumblebee2 stereo system, a) is the source of chromatic images and b) their depth map [3]

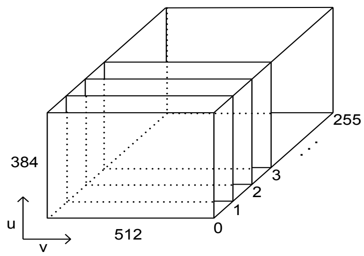

Fig. 4. Depth image layer levels

Near objects will have greater separation (disparity) and appear lighter while far objects will line up very close and appear darker as seen in Figure 3(b). Distance is inversely proportional to disparity. The information contained in the disparity maps is stored in the first 64 gray levels but, in general, there may be more pixel values (gray levels) under different circumstances such as outdoor scenes, or changes in camera calibration. Levels 240 to 255 are reserved for invalid bits, and 0 is used for points at infinity. These values are ignored in our analysis and zero values don't need to be processed and generally appear in white. Disparity maps must be processed to obtain depth information and extract object position, according to

$$z = \frac{f * B}{d}, \qquad (3)$$

where z is the depth, f is the focal lengths in pixels, B is the base line in meters and d is the disparity.

Without loss of generalization, consider a disparity map which is 384 pixels high, 512 pixels wide and 256 levels deep (in gray-level). Referring to Figure 4, visualize a depth map as 256 separate images, in which each depth image will have information about the image at that range.

In the proposed algorithm, nearby objects need to be detected and, for practical walking conditions, two distance ranges were chosen; one meter deep is considered as near proximity and the two meter threshold is used for first detection. According to (3) and camera settings (f=0,765731 and B=0,120049) disparity maps are computed for one meter range and two meters range, originating two layers that correspond to disparities of 27 and 16, respectively. Remember that larger disparity values correspond to closer objects. Depending on depth resolution, object size and orientation, objects will generally appear at two or more depth planes.

The proposed algorithm has four steps:

1) Decompose the disparity image with 2D Ensemble Empirical Mode Decomposition;

2) The disparity image is filtered to eliminate higher frequencies containing noise and fine details. This process is achieved in the reconstruction of Ensemble Empirical Mode Decomposition by eliminating the first two IMFs and using root mean square error minimization according to (1),

$$x(t) = \sum_{i=3}^{N} c_i(t) + r_N(t),$$ were i start at 3 IMF;

3) Define two regions of interests (ROIs) near the blind user to ensure safe walk thought possible obstacles. In our case we chose to analyse the depth information at one meter and two meters. Data outside the two ROI are set to zero. This way we get information about surrounding obstacles at two predefined distances;

4) Finally, we apply range image segmentation by combining the information from depth maps with real images to extract object information at those distances.

This procedure will be useful for future object recognition.

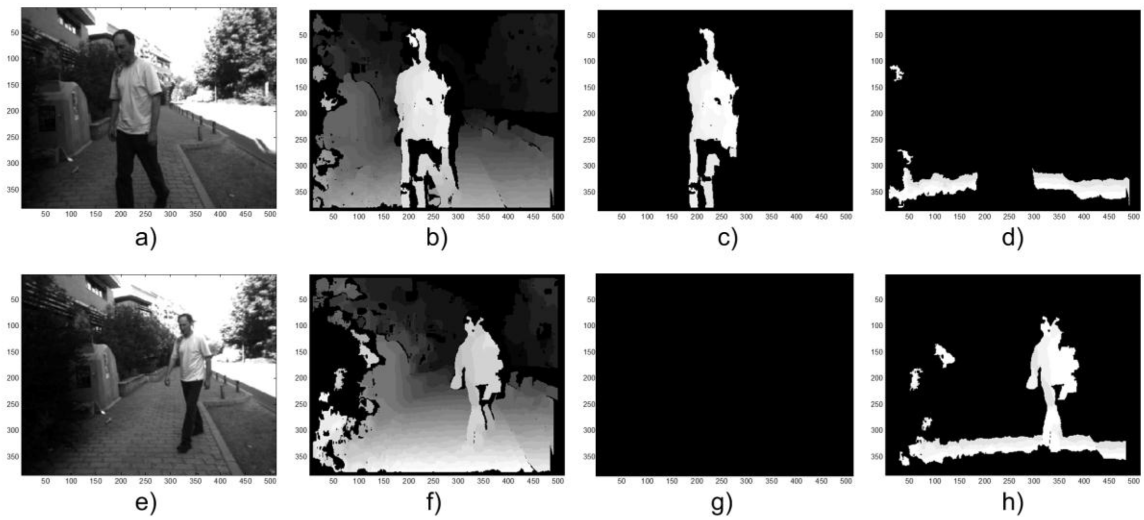

Fig. 5. Results of the proposed algorithm for obstacle detection. Figures a) and e) are real images, b) and f) are filtered EEMD disparity images, c) and g) are disparity images segmented at one meter, d) and h) are disparity images segmented at two meters.

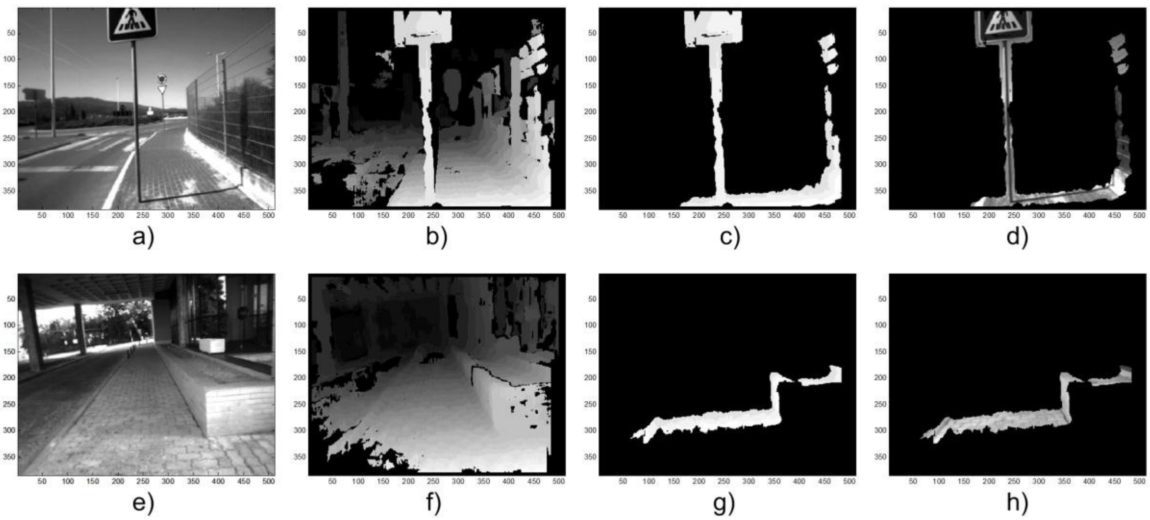

Fig. 6. Results of the proposed algorithm for obstacle detection. Figures a) and e) real images, b) and f) EEMD filtered disparity images, c) and g) segmented disparity at two meters, d) and h) real object segmentation.

4. Experimental results and discussion

In order to test the proposed algorithm, a set of different images were taken on UTAD campus. Figure 5 represents the global results of information extraction. When not avoided, objects near the user may pose a serious danger.

Figures 5a) and 5e) are sample images to be analyzed. Figures 5b) and 5f) are disparity maps processed in the first and second steps of the algorithm. Disparity maps are decomposed, filtered with 2D EEMD to remove noise, fine details and some inhomogeneous illumination present in some stereo images. All values higher than 64 (camera settings) are set to zero in order to obtain a dense disparity map. Figures 5c) and 5g) are segmented disparity maps at distances of about one meter from the stereo camera on which the remaining distance levels are set to zero. Figures 5d) and 5h) represent the same disparity map segmentation but at a distance of two meters away from camera. The main difference to the previous segmentation (1 meter away from the user) is that the ground floor effect appears. In future implementations, this issue needs to be minimized.

Figure 6 shows the described methodology applied to more image samples (6a), 6b), 6c), 6e), 6f) and 6g)). Data from segmented disparity maps is combined with real images to extract useful information from objects, as shows in Figures 6d) and 6h). Using this configuration, the disparity map was segmented at two meters and, as previously, the ground floor effect also appears.

Based on the relative position of the blind user and the detection of the nearest objects in the environment it is possible to compute the trajectory correction and respective output to be given to the blind user. The user interface uses microvibrators that signals corrections corresponding to the five directions: left, left-diagonally, straight, right diagonally and right.

5. Conclusion

In the presented work a computer vision obstacle detection module for the Blavigator project was proposed. For an efficient navigation the CV module must detect accurately specific features in the environment. In outdoor navigation, specifically due to very different possible scenarios, we adopted to implement a two layer obstacle detection and avoidance. The first layer, representing information at two meters in front of the user is intended for object detection, and a second layer, one meter away from the user is used for backup and trajectory correction purposes. Using the stereo vision system it is possible to implement range image segmentation and extract useful information for object detection and recognition.

The Blavigator prototype is also composed by other modules, as seen in Section II and, at the moment, they are all being integrated. The CV module is assembled on a laptop and at the moment it is capable of real time stereo image processing (13 frames per second). In our algorithm EEMD image analysis is used in phases one and two and the system can´t perform in real time. For real time processing future work is needed to define strategies for reduce computational complexity. In addition a set of tests are necessary to be done to the assembled system by blind users to validate and improve the system.

Further work is needed to enhance the overall accuracy, for example to remove or minimize ground floor effects and the implementation of object recognition. Future improvements will continue to use EEMD for image analysis.

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