Wearable RGB Camera-based Navigation System for the Visually Impaired

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Abstract: This paper proposes a wearable RGB camera-based system for sightless people through which they can easily and independently navigate their surrounding environment. The system uses a single head or chest mounted RGB camera to capture the visual information from the current user's path, and an auditory system to inform the user about the right direction to follow. This information is obtained through a novel alignment technique which takes as input a visual snippet from the current user's path and responds with the corresponding location on the training path. Then, assuming that the wearable camera pose reflects the user's pose, the system corrects the current user's pose to align with the corresponding pose in the training location. As a result, the user receives periodically an acoustic instruction to assist him in reaching his destination safely. The experiments conducted to test the system, in various collected indoor and outdoor paths, have shown that it satisfies its design specifications in terms of correctly generating the instructions for guiding the visually impaired along these paths, in addition to its ability to detect and correct deviations from the predefined paths.

1 INTRODUCTION

The World Health Organization (WHO) provided an estimate of the number of visually impaired people around the world in 2014 to about 285 million. This estimate was further split into around 246 million with low vision and 39 million with a total loss of sight. Among blind people, long canes and guide dogs are considered the most widespread navigation aids (Manduchi and Kurniawan, 2011). However, they have a small coverage range and do not provide a clear directional information toward the destination. Recently, computer vision technology has been considered as an effective and cheap alternative for blind assistance, in navigation and way finding. However, most of the existing systems are inaccessible to all individuals either due to their design complexity or high computation cost. As a result, they need much more training efforts from the blind users before adopting them. Also, as they mainly depend on multiple sensors for capturing data from surrounding environment, the decisions based on these data may be not guaranteed and the blind person relies on his estimation for the safe path. In addition, the majority of these systems are either applicable for indoor or outdoor environments due to their different natures.

In this paper, we introduce a new mono RGB camera-based navigation system for the majority of the blind people. The system assists the blind individuals to independently navigate their routine paths till they reach safely to their destinations. It also alarms the users in case any deviation from the predefined paths is detected and informs them with the correct direction to follow within a reasonable time. By the end, The system is evaluated through testing on a various collected indoor and outdoor routine paths with the help of a number of volunteers.

The rest of this paper is organized as follows: Section 2 reviews the existing vision-based navigation systems for the blind people and the video alignment techniques. Section 3 introduces an overview of the different system's components, in addition to a detailed description of the software modules. The proposed system is evaluated and the results are discussed in Section 4. Finally, conclusion and future work are given in Section 5.

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2 RELATED WORKS

2.1 Video Alignment

The aim of video alignment is to find the corresponding frames in two given videos, called the reference and the observed video, respectively. Unlike image alignment techniques, space and time must be considered in case of aligning two sequences. Specifically, synchronization or temporal alignment refers to mapping each frame in the observed video to its most similar corresponding frame in the reference sequence (Diego et al., 2011). Video alignment is a common problem in many computer vision applications such as video editing (Wang et al., 2014), change detection (Diego et al., 2011), action recognition (Ukrainitz and Irani, 2006), and abandoned objects detection (Kong et al., 2010). In this work, the video alignment applications are extended to include real time navigation of blind individuals.

Most of the previous video alignment methods rely on stationary or rigidly connected cameras. Besides, they suppose that the trajectories of moving points along the video are known (Padua et al., 2010; Wolf and Zomet, 2006) or the existence of some linear relationship between the two corresponding videos (Tresadern and Reid, 2009; Ravichandran and Vidal, 2011; Padua et al., 2010). Our work considers a more complex video alignment problem. Specifically, our scenario is to synchronize two videos which are acquired from two independently moving cameras following the same path such that an overlapping field of view exists among the two videos.

2.2 Navigation Systems

Electronic travel-aid (ETA) systems have been introduced to provide the blind person with a more comfortable and independent mobility style than the traditional aids like white cane and guide dog. They can be categorized according to how they sense the surrounding environment and the modality through which they communicate with the disabled person. Sensing the environment can be through laser (Yuan and Manduchi, 2005), ultrasound (Laurent and Christian, 2007), or vision sensors, while communication with the user can be either through an auditory or tactile interface. Although, the majority of ETA systems were designed to replace or enhance the functionality of the white cane, they cannot avoid the user's head level-obstacles in many situations.

Recently, many researchers are focusing on using computer vision techniques as a less costly and more effective solution for blind people assistance in their real navigation. All works in this area can be classified along three directions: the stereo, RGB-D, and RGB camera-based navigation systems. Stereo based systems (Saez et al., 2005; Martinez and Ruiz, 2008; Sáez and Escolano, 2011), estimate a user's motion by considering the camera trajectory. They also exploit the visual and depth information acquired by the stereo sensors to build a 3D map of the user's surroundings for successful path planning or obstacle detection. As these systems are either chest or shoulder mounted, they may need the body rotation for scanning the user's surrounding environment. In 2010, Pradeep et al. have introduced the first real time head mounted stereo-based navigation system for the visually impaired (Pradeep et al., 2010). The head mounted style provides its user with a more comfortable way to traverse his surroundings, whereas the wearable tactile vest interface keeps him away from the obstacles. Although most of the stereo-based travel-aid systems have been proved to be effective in certain environments, they suffer from some shortcomings. First, they do not perform well in environments with low textures like white walls. Also, they provide the sightless individual with an estimation of the safe path due to the quantized depth information acquired from the stereo sensors. In addition, they require an excessive computational costs for constructing the depth maps for a successful navigation, especially in cluttered environments.

Compared to the stereo-based systems, single camera-based systems are more compact and easier to maintain. In this respect, Lee and Medioni used the RGB-D camera as an alternative to the stereo in (Lee and Medioni, 2011; Lee and Medioni, 2014) and proposed a real time navigation system for the blind people. The system enabled the sightless people to detect obstacles in indoor environments with a wider range of detection than of white canes or stereo-based systems. Recently, in 2016, another RGB-D-based system (Aladren et al., 2016) has been proposed. The authors exploited the combination of the depth information and the image intensities for extending the range of depth information aiming at detecting far obstacles. In addition, the system enables the blind person to safely navigate the challenging and unknown indoor paths. Concurrently, Lee and Medioni introduced another complete real time system for the blind individuals navigation (Lee and Medioni, 2016). The system estimates the shortest safe path to the user's destination through generating the appropriate real time maps for his surrounding environment. The blind user defines his current and goal location to the system via some mobile interface. Then, the system responds with an appropriate cue which alerts the user through a tactile system toward the generated safe path. In contrast to the stereo-based navigation systems, the majority of RGB-D -based systems achieve accurate results in case of indoor environments even for those with low textures. Besides, they require less processing time for generating the depth maps. However, they are not applicable to the outdoor environments.

As an extension to a mono camera-based systems, RGB cameras have been adopted for assisting the visually impaired in navigation instead of stereo or RGB-D cameras. In 2008, an RGB camera-based indoor deviation detection system has been proposed for the blind users (Pathangay, 2008). The system maps, at run time, the captured input from the current user's scene to its corresponding scene in a predefined path, using the dynamic time warping algorithm. Then, the path deviation can be detected when the similarity score average in a defined detection window is below some defined threshold. However, this method suffers from some defects. First, it often detects the deviations among various indoor paths with a high delay that reaches up to hundred frames. Also, it can not provide the user with a corrected direction to follow in case of deviation detection. Moreover, it falsely alarms the user about the existence of deviation in the current path with a high rate, as a little change in camera's pose may cause a higher ratio of dissimilarity. Recently, an Android navigation application was introduced for the sightless individuals depending on the smart phone's camera (Idrees et al., 2015). It starts by defining the current user's location through scanning one of the existing QR codes on the floor along the indoor path. Consequently, it generates the shortest and optimal path toward the user's destination. In addition, it can detect and correct the user's deviation from the predefined path. Unfortunately, the system is not practical for outdoor paths as it needs to cover the whole path's width by horizontal tapes of QR codes to avoid the scanning problem. More recently, a new smart phone-based system has been introduced for assisting the sightless people to find their way to their destinations in unknown indoor environments (Ko and Kim, 2017). Upon defining the target destination, the system starts by classifying the type of current user's place. Accordingly, it begins by localizing the QR code which exists at a specific location based on the place type and then fetching the code information which may be either location or directional code. After that, the system provides the user wsome guidance instructions via a text to speech service. In addition, it enables the user to go back to his starting location after reaching the destination through storing its trajectory to the destination, with the aid of some inertial sensors in the phone.

In this paper, we propose a new navigation system targeting the majority of blind people. It depends only on the appearance information from the user's environment captured through a mono RGB camera sensor to help the blind user to reach safely to his destination. Also, without additional sensors, the system can operate in both indoor and outdoor environments.

3 SYSTEM DESCRIPTION

In this section, we introduce an overview of the different hardware and software components of the proposed system, as shown in Figure 1.

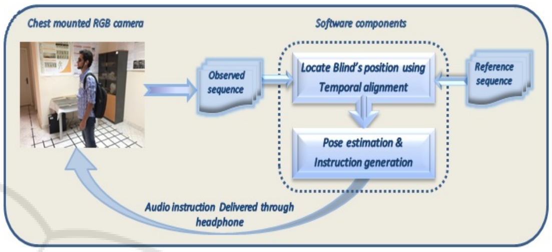


Figure 1: Overview of the proposed navigation system.

3.1 Hardware Components

The system is composed of three main components: a chest/head mounted camera, a laptop kept in the blind's knapsack, and a wearable headphone. The wearable camera acquires a snippet from the current blind's path to be processed by the navigation system. Then, the system generates an audio instruction and delivers to the blind user via a simple wearable headphone, in order to guide him toward the destination.

3.2 Software Components

The proposed system consists of two major modules: (i) the temporal alignment module which is responsible for locating the current blind's position w.r.t to a training video. (ii) the pose estimation and instruction generation module which generates an audio instruction for the user to follow to remain consistent with his pose at the same location in the training video.

3.2.1 The Temporal Alignment Module

In contrast to the proposed alignment technique which relies on a moving camera, most of the prior video alignment techniques depend on stationary or rigidly connected cameras. We also suppose that the observed video is contained in the reference video. As a result of applying the proposed technique, each frame from the input sequence is mapped to the one with the maximum similarity score in the reference sequence. More specifically, upon capturing a small snippet from the current scene in some path, the blind individual's location is defined in the corresponding training video using the proposed technique.

Consider two sequences F_m^O and F_n^R where F_m^O represents the observed video with length M, m= [1...M] and F_n^R represents the reference video with length N, n= [1...N]. The issue is to find the mapping among these two videos.

In our work, we propose a new dynamic programming formulation for solving the alignment problem which is considered the main step for our navigation system. Practically, consider that i refers to a specific frame in the observed sequence and j its corresponding frame in the reference sequence. For obtaining an accurate mapping between these two frames, the history of the previous frames' mapping till the current observed frame is considered, as indicated in Eq.(1). Also, as our system is designed for online operation and needs to make a decision with each observed frame, so the observed frame should be included in the calculations of finding its corresponding frame, as shown in Eq.(2).

$$MS(i,j) = max \begin{cases} MS(i-1,j-1)+Sim(i,j) \\ MS(i-1,j) \\ MS(i,j-1) \end{cases} \quad (1)$$

$$MS_{last}(i,j) = max \begin{cases} MS(i-1,j-1)+Sim(i,j) \\ MS_{last}(i,j-1) \end{cases} \quad (2)$$

Where $Sim(i,j)$ represents the similarity score between the i^{th} and j^{th} frames.

Regarding the calculation of the similarity measure, we rely on the spatial pyramid matching technique introduced in (Lazebnik et al., 2006). It is an effective technique for image representation and is proved to be better than other existing image descriptors like SIFT and gist. This technique works by considering the image at different levels $l = 0,1,...,L-1$, where l represents a specific image's level. Each level is partitioned into a number of sub grids such that the total number of grids in that level is $D = 2^l$. Specifically, we want to provide a score representing to what extent frames i and j are similar using the spatial pyramid technique. Firstly, the total number of matching among the two frames at a specific level is found by calculating the gray-scale histogram intersection between each corresponding sub-grid, using Eq.(3).

$$I^l = \sum_{d=1}^{D} min(H_i^l(d), H_j^l(d)) \quad (3)$$

Where $H_i^l(d)$ and $H_j^l(d)$ represent the histograms of the two corresponding sub-grids, d, for the two frames at a specific level l, respectively.

Then, the pyramid match kernel which is the sum of the weighted histogram intersections for all levels of the two intended frames is obtained using Eq.(4). Clearly, each level is weighted inversely proportional to the wideness of its cells, $\frac{1}{2^{L-l}}$, aiming at giving more penalty to the matching occurring at wider cells.

$$K^L(i,j) = \frac{1}{2^L} I^0 + \sum_{l=1}^{L} \frac{1}{2^{L-l-1}} I^l \quad (4)$$

After that, in order to obtain the final spatial kernel which represents the similarity score among i, j frames, we consider the different features which completely represent the image. Specifically, each component in the pyramid kernel, given in Eq.(4), represents a separate kernel for one feature, and the spatial kernel is the sum of all separate kernels, as follows in Eq.(5):

$$Sim_{score}(i,j) = K^L(i,j) = \sum_{t=1}^{T} K^L(i_t, j_t) \quad (5)$$

Where $K^L(i_t, j_t)$ is the kernel of feature type t, and T is the total number of the different image features.

3.2.2 Pose Estimation and Instruction Generation

This step is responsible for extracting the right instructions for the blind person during his navigation along the path, according to a predefined path. In order to estimate these instructions, we consider that the current pose of the wearable camera provides an estimate of the current user's pose. Once the system defines the user's location w.r.t a training path using the proposed alignment technique, it starts to estimate his pose at that defined location. This is estimated as the relative camera pose between the training frame which reflects the user's location and the frame following it by a time duration sufficient to reflect the right pose. Experimentally, this duration is found to be two seconds for the outdoor path and half a second for an indoor path.

The pose estimation process depends mainly on the matching process between two frames and using some similarity measure. We have chosen the Speeded Up Robust Features (SURF) technique which is invariant to both scale and rotation during the interest points detection and feature vectors extraction (Bay et al., 2008). In order to estimate the best model that fits most of the space points, i.e. maintain only the inliers or the true matches, and exclude the outliers, the best choice is the Random sample

Consensus (RANSAC) algorithm (Fisher, 2002). But, in our problem, we use the optimal RANSAC algorithm (Hast et al., 2013), which outperforms the traditional algorithm for the following reasons. It performs well in finding the optimal inliers' set, even when the percentage of inliers' number is as low as 5% of the total matches. Unlike the traditional RANSAC which requires this percentage to exceed 50% for best results. In addition, it returns the optimal set each time with a slight difference whatever the number of runs, especially with aerial images. However, it follows the standard RANSAC in case of multiple plane-images. Finally, through using both the inliers, the estimated model, and the camera parameters, the current pose for the blind user is estimated. Experimentally, through using shots with various camera poses for the same scene, we determine the suitable range of angles for each individual's pose which are expressed by one of five meaningful directions, go straight, take right, take left, slightly right, and slightly left. By the end, our proposed system enables the blind individual to safely navigate along indoor and outdoor paths without any human aid or extra sensors, through periodically providing him with an assistive instruction within a reasonable time.

4 EXPERIMENTS AND RESULTS

4.1 Dataset Collection

Our dataset is collected such that it contains various pairs of indoor and outdoor paths with different lengths, six pairs for each. All outdoor paths are captured at our campus, under various illumination conditions and with different start and end points. While, the first four pairs of the indoor paths are recorded at our cyber-physical systems lab, starting from the same point, but with different destinations: whiteboard, printer, door, and the meeting room, respectively. And the last two are captured at an apartment to add some variety to our dataset.

4.2 Experiments

The proposed system is tested using the HTC Desire 820 G PLUS dual sim-chest-mounted-camera with 13 megapixels, (720x1280) resolution, and (1080p@30fps) video camera. It runs on a machine with the following configurations: CPU: Intel(R) Core(TM) i7-4700 MQ @ 2.40 GHz, RAM: 8.00 GB, and OS: Windows 10- 64 bit.

The performance of the system depends mainly on the output of the proposed alignment technique introduced in section 3.2.1. In other words, the more accurate the blind's location is determined by the alignment technique, the more successful is the estimation of the user's pose, and the more probable the correct guiding instruction is generated. The first experiment tests the alignment technique's ability in determining the correct user's location in both indoor and outdoor training sequences, respectively. In the second and third experiments, the system's accuracy is evaluated regarding releasing the correct real time instructions for the blind user as well as detecting and correcting the user's deviation from the predefined paths, respectively. For more implementation details.[1]

4.2.1 Experiment 1

This experiment tests the proposed alignment technique in defining the current user's location. Given an observed sequence from the user's surroundings, our technique proves its efficiency in mapping each observed frame to its corresponding one in the reference sequence in case of indoor and outdoor environments, as shown in Figures 2, 3, respectively.

Figure 2: Example for Indoor Alignment. (a) Selected frames from the observed video. (b) The corresponding frames retrieved from the reference video (after temporal alignment). (c) Fusion Image (Red and Blue channels of color image are assigned to the observed frame, while the Green channel is assigned to the reference frame).

Figure 3: Example for Outdoor Alignment. (a) Selected frames from the observed video. (b) The corresponding frames retrieved from the reference video (After temporal alignment). (c) Fusion Image (as in Figure 2).

[1]All experiments are implemented in MATLAB, using Computer Vision Toolbox and re-sized images (80x60). Also, all videos are sampled such that three frames per five are selected in training videos while three frames per ten in testing videos, for speeding up the alignment step.

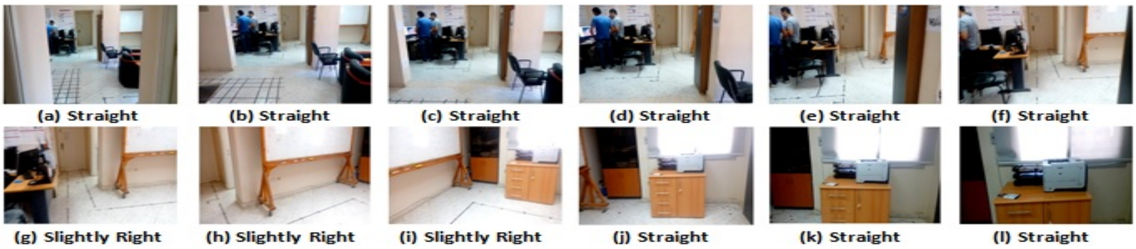


Figure 4: Example for Indoor Path instruction generation.

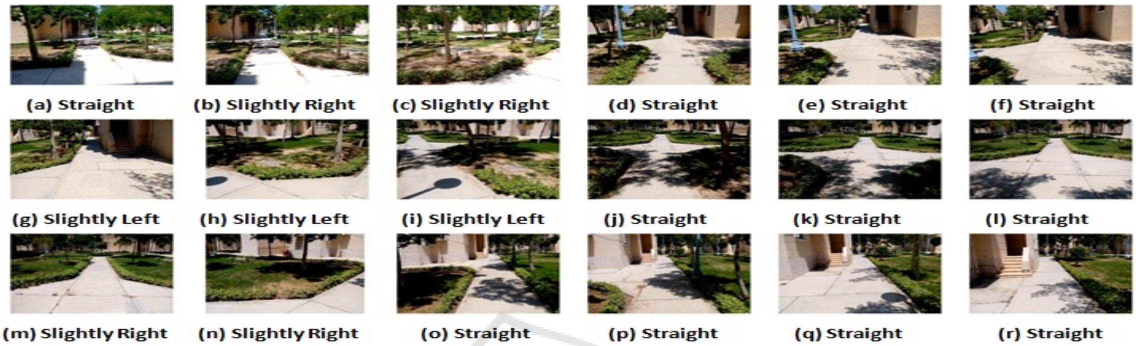


Figure 5: Example for Outdoor Path instruction generation.

4.2.2 Experiment 2

This experiment evaluates the system's ability to generate the right instruction for the blind user every specific period of time, which amounts to one second, according to a predefined path. For this task, we construct a voting system for each path in the dataset with the help of a group of seven individuals. This voting system reflects the instruction that should be taken at each selected frame from the real path according to the majority of the individuals' opinion. Then, the generated instructions from our system are compared with these reference instructions for the same path and the system's accuracy is calculated. Table 1 presents the system's accuracy in generating the correct instructions during navigating various indoor and outdoor routine paths.

Table 1: System's Accuracy in generating instructions.

(a) Outdoor

Path	Accuracy%
Path1	97.06%
Path2	95.45%
Path3	97.92%
Path4	97.37%
Path5	93.55%
Path6	97.73%

(b) Indoor

Path	Accuracy%
Path1	100%
Path2	100%
Path3	95%
Path4	100%
Path5	95.45%
Path6	100%

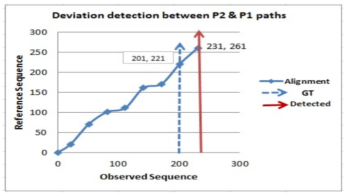
Regarding the results of Table 1a, the system achieves a high accuracy in most of the dataset paths. However, the main reason behind the accuracy drop in some outdoor paths is either the scene occlusion or the high illumination variance between training and testing sequences. As these reasons may cause failure in generating the guidance instructions at some positions in these paths, our system provides the user with stop instructions to avoid any troubles. Also, as the system generates periodically, every one second, an instruction, so in most cases this failure does not last along the whole path and the system recovers quickly its normal state in generating the assistive instructions for the blind user. Although our system can efficiently handle the small changes in the camera pose resulting from the normal movements of the user, unstable and sudden movements which may cause big changes in the camera pose are unacceptable and make the system fail to understand the surrounding environment. This problem is considered as the common cause of the slight reduction in some paths' accuracy which may result in a partial failure of the system to generate correct instructions in some positions along either outdoor/ indoor paths, as shown in Table 1.

For more explanation, Figures 4 and 5 demonstrate the generated instructions for the sightless individual along some parts of path2 and path6 from the indoor and outdoor paths in the dataset, respectively.

4.2.3 Experiment 3

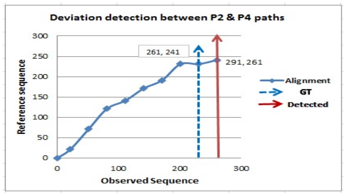
This experiment measures the system's accuracy in detecting the user's deviation from a predefined path, within two scenarios: 1) The training and testing videos describe the same path. 2) The training and

(a) Deviation detection between path P2 & P1



(b)

(c) Deviation detection between path P2& P4



(d)

Figure 6: (a,b) Two examples for Indoor Deviation Detection between path2, in Figure 4, and both path1 & path4, where Blue and Red squares represent the ground truth and system detection, respectively. Two graphs (b,d) show the system's delay in detecting deviation between these paths.

testing videos describe two different paths. Regarding the first scenario, it measures the system's accuracy in providing the user with a false alarm-deviation detection. While the second scenario measures the accuracy of the system in detecting the user's deviation as a true alarm. To achieve this experiment, we build the ground truth by asking five individuals to mark when the deviation starts to occur by applying the second scenario in all dataset paths.[2]

For the first scenario, the system results in no deviation detection, leading to an accuracy of 100%. In other words, the proposed system does not suffer from generating false alarm decisions. On the other hand, the second scenario results in detecting the existing deviations between all various paths in the dataset, with an accuracy of 85.8%. In addition, the delay taken by the system to detect a path deviation is one second on average, as shown in Figures 6b and 6d. This performance is better than that given in (Pathangay, 2008), which detects the deviation with a delay of the order of a hundred frames, i.e. ranging from three to four seconds. It is worthy to mention that, the proposed system achieves the same deviation detection accuracy, even with small similarity score thresholds, like 0.2 and 0.3.

[2]The similarity score threshold is set to 0.4 in the alignment step and the deviation is detected when there is no enough number of inliers among the current corresponding frames' pair during the pose estimation step.

5 CONCLUSION AND FUTURE WORK

In this paper, we have introduced a new assistive navigation system to help most of the visually impaired with an effective and cheap solution. The system relies on a single RGB camera as an input device and a simple headphone to deliver the generated instructions to the blind user. Also, We have presented a new alignment technique to determine the user's location by referring to a training video for the current path. Then, through determining the user's pose in that defined location, the system can generate an acoustic instruction for guiding the sightless user. The system has been tested on various indoor and outdoor paths. Consequently, it achieves a high accuracy in guiding the blind people toward their destinations. Moreover, it reflects an accurate and quick response to alarm the user whenever he deviates from a predefined path and provides him with the corrected direction.

Our navigation system can be enhanced by considering the following: more optimization for compatibility with real-time devices, supporting more complex and cluttered paths, and detecting the existing holes, stairs, and obstacles in the user's path.

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REFERENCES

Aladren, A., López-Nicolás, G., Puig, L., and Guerrero, J. J. (2016). Navigation assistance for the visually impaired using rgb-d sensor with range expansion. *IEEE Systems Journal*, 10(3):922–932.

Bay, H., Ess, A., Tuytelaars, T., and Van Gool, L. (2008). Speeded-up robust features (surf). *Computer vision and image understanding*, 110(3):346–359.

Diego, F., Ponsa, D., Serrat, J., and López, A. M. (2011). Video alignment for change detection. *IEEE Transactions on Image Processing*, 20(7):1858–1869.

Fisher, R. B. (2002). The ransac (random sample consensus) algorithm. *ac. uk/rbf/CVonline/LOCAL_COPIES/FISHER/RANSAC/ index. html,[Access 23-May-2006]*.

Hast, A., Nysjö, J., and Marchetti, A. (2013). Optimal ransac-towards a repeatable algorithm for finding the optimal set.

Idrees, A., Iqbal, Z., and Ishfaq, M. (2015). An efficient indoor navigation technique to find optimal route for blinds using qr codes. In *Industrial Electronics and Applications (ICIEA), 2015 IEEE 10th Conference on*, pages 690–695. IEEE.

Ko, E. and Kim, E. Y. (2017). A vision-based wayfinding system for visually impaired people using situation awareness and activity-based instructions. *Sensors*, 17(8):1882.

Kong, H., Audibert, J.-Y., and Ponce, J. (2010). Detecting abandoned objects with a moving camera. *IEEE Transactions on Image Processing*, 19(8):2201–2210.

Laurent, B. and Christian, T. N. A. (2007). A sonar system modeled after spatial hearing and echolocating bats for blind mobility aid. *International Journal of Physical Sciences*, 2(4):104–111.

Lazebnik, S., Schmid, C., and Ponce, J. (2006). Beyond bags of features: Spatial pyramid matching for recognizing natural scene categories. In *Computer vision and pattern recognition, 2006 IEEE computer society conference on*, volume 2, pages 2169–2178. IEEE.

Lee, Y. H. and Medioni, G. (2011). Rgb-d camera based navigation for the visually impaired. In *RSS 2011 RGB-D: Advanced Reasoning with Depth Camera Workshop*, pages 1–6.

Lee, Y. H. and Medioni, G. (2014). Wearable rgbd indoor navigation system for the blind. In *European Conference on Computer Vision*, pages 493–508. Springer.

Lee, Y. H. and Medioni, G. (2016). Rgb-d camera based wearable navigation system for the visually impaired. *Computer Vision and Image Understanding*, 149:3–20.

Manduchi, R. and Kurniawan, S. (2011). Mobility-related accidents experienced by people with visual impairment. *AER Journal: Research and Practice in Visual Impairment and Blindness*, 4(2):44–54.

Martinez, J. M. S. and Ruiz, F. E. (2008). Stereo-based aerial obstacle detection for the visually impaired. In *Workshop on Computer Vision Applications for the Visually Impaired*.

Padua, F., Carceroni, R., Santos, G., and Kutulakos, K. (2010). Linear sequence-to-sequence alignment. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 32(2):304–320.

Pathangay, V. (2008). Detecting deviations in visual path following for indoor environments. In *TENCON 2008-2008 IEEE Region 10 Conference*, pages 1–5. IEEE.

Pradeep, V., Medioni, G., and Weiland, J. (2010). Robot vision for the visually impaired. In *Computer Vision and Pattern Recognition Workshops (CVPRW), 2010 IEEE Computer Society Conference on*, pages 15–22. IEEE.

Ravichandran, A. and Vidal, R. (2011). Video registration using dynamic textures. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 33(1):158–171.

Sáez, J. M. and Escolano, F. (2011). 6dof entropy minimization slam for stereo-based wearable devices. *Computer Vision and Image Understanding*, 115(2):270–285.

Saez, J. M., Escolano, F., and Penalver, A. (2005). First steps towards stereo-based 6dof slam for the visually impaired. In *Computer Vision and Pattern Recognition-Workshops, 2005. CVPR Workshops. IEEE Computer Society Conference on*, pages 23–23. IEEE.

Tresadern, P. A. and Reid, I. D. (2009). Video synchronization from human motion using rank constraints. *Computer Vision and Image Understanding*, 113(8):891–906.

Ukrainitz, Y. and Irani, M. (2006). Aligning sequences and actions by maximizing space-time correlations. *Computer Vision–ECCV 2006*, pages 538–550.

Wang, O., Schroers, C., Zimmer, H., Gross, M., and Sorkine-Hornung, A. (2014). Videosnapping: Interactive synchronization of multiple videos. *ACM Transactions on Graphics (TOG)*, 33(4):77.

Wolf, L. and Zomet, A. (2006). Wide baseline matching between unsynchronized video sequences. *International Journal of Computer Vision*, 68(1):43–52.

Yuan, D. and Manduchi, R. (2005). Dynamic environment exploration using a virtual white cane. In *Computer Vision and Pattern Recognition, 2005. CVPR 2005. IEEE Computer Society Conference on*, volume 1, pages 243–249. IEEE.