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The Usage of the BP-Layers Stereo Matching Algorithm with the EBCA Camera Set

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ABSTRACT

This paper is concerned with applying a stereo matching algorithm called BP-Layers to a set of many cameras. BP Layers is designed for obtaining disparity maps from stereo cameras. The algorithm takes advantage of convolutional natural networks. This paper presents using this algorithm with a set called Equal Baseline Camera Array. This set consists of up to five cameras with one central camera and other ones aground it. Such a set has similar advantages as a stereo camera. In particular this equipment is suitable for providing 3D vision for autonomous robots operating outdoors. The research presented in this paper shows the extent to which results of using BP Layers are improving because of using the EBCA set instead of a stereo camera.

Keywords

camera array; stereo matching; stereo camera; disparity map; 3D scanning;

1 INTRODUCTION

This paper contributes to the development of 3D vision technologies for autonomous robots. This kind of robots are able to interact with their surrounding and to perform tasks without being directly controlled by human operators. A crucial module of such a robot is its vision system because it makes it possible for the robot to locate in 3D space objects with which it is interacting.

This paper presents research on a 3D vision system based on EBCA (Equal Baseline Camera Array) [Kac15, Kac19]. It is a camera array which consists of up to 5 cameras. Images from such an array are processed as if they were taken by a set of stereo cameras. The description of this array is presented in Sect. 3. The main application of the array is using it for robotic fruit harvesting in which autonomous robots can locate and pick up fruits without being directly controlled by human operators. However EBCA can be also applied to other kinds of robots, in particular those operating underwater [KB21].

The novelty of the research presented in this paper lies in using the EBCA set with the BP Layers (Belief Propagation Layers) algorithm [KSS+20]. BP Layers was proposed by authors from Graz University of Technology located in Austria and Czech Technical University in Prague. It is the algorithm which takes advantage of convolutional neural network in order to make it possible to determine locations of objects in 3D space on the basis of images from a stereo camera. The description of this algorithm is presented in Sect. 2.3.

The presented research describe the method of adapting the BP Layers algorithm to EBCA. BP Layers were originally developed for stereo cameras. EBCA is a set with a greater number of cameras. Therefore, it is necessary to apply a method which would make it possible for the BP Layers algorithm to take advantage of all images from the EBCA set instead of only two images taken by a single stereo camera. The method selected for this purpose is EEMM (Exception Excluding Merging Method) which is described in [Kac17c]. Experiments show that the application of this method reduces on average 22.18% of errors occurring in the results of BP Layers obtained from a single stereo camera.

2 RELATED WORK

Stereo vision is one of technologies which makes it possible to locate objects in the 3D space and to determine their shape. There are many other methods designed for this purpose, however stereoscopy has some unique features which makes it particularly useful in some circumstances. Methods alternative to stereo cameras include using structured light 3D scanners, Light Detection and Ranging (LIDAR) and methods based on multi-view stereo vision (MVS) [GIV10, RCG21, SCD+06]

2.1 Equipment for 3D scanning

Devices which are the main alternative to stereo cameras are Structured light 3D scanners [GIV10]. Structured light 3D scanners provide data regarding location and shape of object with a very high quality. The main feature of light scanners is such that they emit light patters in order to perform a measurement. As a consequence it is problematic to use 3D light scanners when they are exposed to intensive sunlight. Sunlight interfere with procedures performed by a scanner causing that a scanner needs to be equipped with a high intensity light source in order to make it possible to use it in sunlight. However, even with such a significant light source it is problematic to use these devices when objects are not in a close vicinity of a scanner. These problems do not occur when stereo cameras are used. They can be used in daylight and for large distances.

Another equipment which can be used for locating objects and determining their shape are laser based devices using LIDAR [RCG21]. LIDAR is based on emitting rays of lasers in a set of different direction and recoding distance from each point included in the measurement. LIDAR devices can operate outdoor however their disadvantage is such that they have much lower resolution then stereo cameras. It is related to a problem with precisely aiming a laser beam in appropriate direction. The resolution of cameras mainly depends on their sensor size and lens. It is easier and cheaper to achieve high resolution data with cameras then with devices using LIDAR.

A 3D shape of objects can be also determined with the use of the multi-view stereo (MVS) technology [SCD+06]. In this method it is required to make a set of images of an object for which a 3D scan is obtained. This images need to be taken by placing camera in different points of view located around the object. On the basis of these images the MVS algorithm determines locations of cameras at the moment of taking images and then the algorithm calculate the shape of objects by matching in images locations of the same parts of a real object. These parts needs to be visible in many images included in the processed set. The problem with the MVS technology is such that it requires to take images from around the scanned object. It is not possible to perform such a procedure in every situations. In particular it is problematic when an autonomous robot has to locate some distant objects like in case of an autonomous car operating on a street. Stereo cameras retrieve data about the distance to objects and their parts without the necessity to more the device around these objects.

2.2 Stereo cameras

Images from a stereo camera need to be processed in order to estimate distances similarly as in case of MVS. Retrieving distances to objects visible in images consists of two steps. In the first step, a stereo matching algorithm identifies in two images locations of the same parts of real objects. In order to achieve this cameras are distinguished between a reference camera and a side camera. Locations of cameras are different therefore relative locations in two images of the same objects is also different. It does not apply only to objects which are located so far away from a stereo camera that their location on both of images is the same. This difference in locations of corresponding parts is called disparity. A set of all found disparities for a reference image forms a disparity map [HI15, Kac19].

Values of disparities indicates distance to objects. The closer the object is to a stereo camera the greater will be a disparity. Taking into account parameters of a stereo camera such a distance between its cameras called baseline and focal length of lens disparities can be converted to distances forming a depth map.

A stereo matching algorithm searches in a side camera for areas with the lowest matching cost for every point of a reference image. In general stereo matching algorithms perform a local matching which means that the search for a corresponding area is performed only in a part of a side image in which it is expected that a matching area is present. After performing local matching most of stereo matching algorithms performs global matching in which disparities are optimized globally. In this step disparities are modified with respect to values of disparities in their vicinities. One of the method of global optimization of disparities is based on Markov Random Fields (MRF) [SS02, Bes86]. MRF is a method from which the BP Layers algorithm is derived. It is the algorithm which is used in experiments presented in this paper.

The problem with stereo matching is such that algorithms do not correctly match all points of a reference image with points of a side image. This causes errors in values present in disparity maps obtained as a result of matching. A large number of stereo matching algorithms have been developed in order to find the best methods. There are also rankings of this kind of algorithms. The post popular rankings of stereo matching algorithms are Middlebury Stereo Vision (`https://vision.middlebury.edu/stereo/eval3/`) and KITTI Vision Benchmark Suite (`http://www.cvlibs.net/datasets/`

kitti/ [SSZ01, SS02, SHK+14, GLU12]. The first ranking consists of over 190 algorithms the latter lists over 300 ones.

2.3 BP Layers algorithm

The BP Layers algorithm improves previously developed BP algorithm with the technology of convolutional natural networks. BP was proposed by Tappen and Freeman in [TF03]. It is a method for globally optimizing disparities using the concept of MRF and Conditional Random Fields (CRFs) [LMP01]. In order to develop the algorithm and to perform experiments authors of BP Layers took advantage of many important stereo matching algorithms including Belief Propagation (BP) [TF03],tree-structured dynamic programming [BG08] and semi-global matching [Hir08].

BP layers was implemented with PyTorch using the CUDA architecture. In order to train the network authors of BP layers used data released by authors of rankings of stereo matching algorithms. Rankings provide testbeds and benchmarks. The main part of such a testbed are sets of images taken be a stereo camera and ground truth containing correct values of disparities which stereo matching algorithms should obtain after processing image pairs. These input images and correct values are crucial data for training neural networks. BP Layers was executed using Middlebury Stereo Vision and KITTI test data.

3 EQUAL BASELINE CAMERA ARRAY

Equal Baseline Camera Array was deigned to address the problem with errors occurring on disparity maps obtained on the basis of images from a stereo camera [Kac15, Kac17a, Kac17b]. EBCA preserves all the benefits of a stereo camera however simultaneously EBCA provides higher quality of data than a stereo camera. Park and Inoue were the first ones who proposed using this kind of a camera set [PI98]. Information regarding other researchers working with this set can be found in [KB21].

EBCA is a set of cameras with consists of a central camera and up to four side cameras located around the central one. The baseline is the same in every this kind of a camera pair. All cameras in the set are aimed in the same direction. Cameras in EBCA are regarded as if they create a set of up to four stereo cameras such that each one of them consists of the central camera and one of side cameras. Therefore all these stereo cameras share the same camera which is a central one. This camera has a function of a reference camera in all of these considered camera pairs. They will be marked with S_i, $i \in 1,2,3,4$. The maximum value of i depends on the number of side cameras included in the set. The

Figure 1: The real EBCA set used in experiments

real EBCA used in experiments is presented in Fig. 1 [Kac19]. It consists of MS LifeCam Studio cameras.

Using EBCA resembles making many measurements of the same distance using cameras S_i. These measurements are partly independent as cameras S_i share a central camera, but they consists of different side cameras. Disparity maps can be obtained on the basis of images from each camera S_i. Data acquired from S_i is then processed in order to obtain a single disparity map which contains less errors than any disparity map acquired form a single stereo camera S_i. The method of merging data from cameras S_i is a scientific problem itself because it required developing a method which reduces the amount of errors to the highest possible extent.

4 TESTBED

The author of papers [Kac17c, Kac19] proposed a few algorithms for merging this data. Mainly two kinds of methods were proposed. In the first one disparity maps are calculated on the basis of images from every camera S_i, than data included in these maps is compared and merged in order to acquire a disparity map of a higher quality. The merging method proposed by the author of [Kac17c] was called EEMM (Exception Excluding Merging Method). Method EEMM was used in research presented in this paper because experiments described in [Kac17c] showed that it is the most suitable for adapting stereo matching algorithms to the EBCA set without the necessity to modify the source code of a stereo matching algorithm. In the second type of a merging method the internal structure of a stereo matching algorithm selected for processing data from EBCA is modified in order to adapt it so that the algorithm can simultaneously process all images from EBCA. This method of modifying stereo matching algorithms makes it possible to use parts of stereo matching algorithms as if only two images were processed however other parts of algorithms process

Figure 2: Test images used in the experiments with BP layers applied to EBCA

data from all images simultaneously. This method of adapting stereo matching algorithms to EBCA is described in [Kac19].

A testbed presented in [KB21] was used to evaluate results of applying the BP layers algorithm to EBCA with the use of the EEMM method. The testbed was designed for testing stereo matching algorithms designed for EBCA. The testbed contains six sets of images taken by EBCA presented in Fig. 1. Every set consists of images made from all cameras included in EBCA. These were images of plants with at least one fruit. Plants used for making the testbed were strawberries, cherries and redcurrant. Cameras in EBCA were calibrated using methods described in [KB21]. Apart from images the testbed contains ground truth which provides correct values of disparities which should be acquired as a result of using stereo matching algorithms.

Three sets from the testbed were used for evaluating the BP layers algorithm applied to EBCA. These sets were marked with ST_1, CH_1, RC_1. Figure 2 shows images used for preparing the sets.

Results were evaluated with the use of three quality metrics. These were percentage of bad matching pixels (BMP), percentage of bad matching pixels in background (BMB) and the coverage level (COV) [Kac19]. BMP is the most common quality metric used for evaluating results of stereo matching. It identifies the share of points whose values are within acceptable error margin [SS02].

Another metric used for evaluating results is called BMB [Kac19]. This metric is calculated in the similar way as BMP however only points in the background are taken into account. The background of a reference image is an area for which there are no matching areas in a side image. A reference image may contain views of some objects located behind objects placed in the foreground. Objects in the background are only partly visible. For example such a background is the ground visible between plants leaves. Such areas are however not visible on side images on which other parts of ground can be seen between leaves of a plant located in the foreground. Therefore a stereo matching algorithm is not able to match areas of the background visible on the reference image with areas on a side image. In such a case a stereo matching algorithm should mark on the resulting disparity map that the disparity in this areas in unknown.

The third metric used for evaluating results is called COV [Kac19]. This metric shows the extent to which a resulting disparity map contains disparities with regard to the size of an area in which matching was performed.

5 EXPERIMENTS

The author of this paper performed experiments in order to evaluate results of adapting the BP Layers algorithm to EBCA with the use of the EEMM merging method. Experiments were performed on data sets ST_1, CH_1 and RC_1 presented in Sect. 4. The implementation of BP Layers provided by its authors as used. Experiments presented in this paper were based on the neural network trained with the KITTI 2015 data set. Experiments were performed on a computer with the NVidia GeForce 1060 6GB graphic card. The EEMM method was used to merge data from cameras C_i included in EBCA. EEMM was executed with both of its parameters, i.e. Q and B equal to 5 [Kac17c].

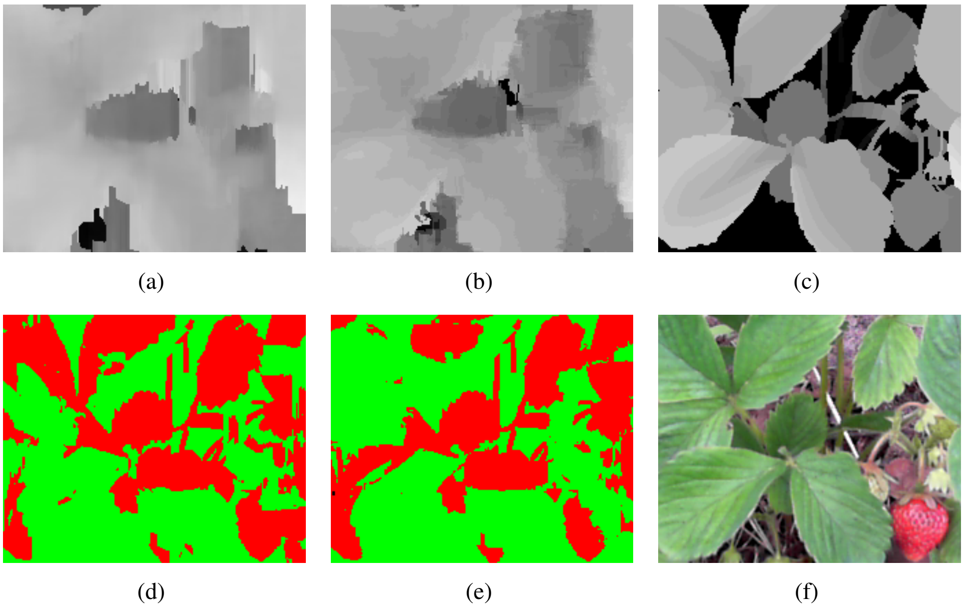

Figure 3: (a) Results of using BP layers with a single stereo camera, (b) Results of using BP layers with EBCA, (c) Ground truth, (d) error map for results presented in (a), (e) error map for results presented in (b), (f) 2D image

Figure 3 presents results obtained for the ST_1 set. Part (a) of this figure shows a disparity map obtained as a result of using original version of BP Layers with a single pair of cameras. Part (b) of Fig. 3 presents a disparity map acquired with the use of EEMM and EBCA with five cameras. These results can be compared with correct values of disparities available in ground truth visualized in part (c). Parts (d) and (e) are error maps generated for results presented in parts (a) and (b) of Fig. 3, respectively. Green color symbolizes areas in which matching was correct. Part (f) shows the image of the analyzed plant. It can be noticed that the disparity map presented in part (b) contains smaller areas with inappropriate values of disparities than the disparity map shown in (a).

These differences in the quality of results were also verified by calculating values of quality metrics described in Sect. 4. The purpose of experiments was to verify the influence of number of cameras included in EBCA on the quality of results. Figure 4 shows values of the BMP metric which was obtained for each data set used in experiments with regard to the number of cameras included in calculations. Figure 4 contains average values acquired as a result of using every possible subset of cameras from 5 camera EBCA show in Fig. 1. For example values for two cameras are average values of BMP calculated on the basis of four disparity maps acquired from stereo cameras S_1, S_2, S_3 and S_4. Similarly, results for other number of cameras are average values based on all possible configurations

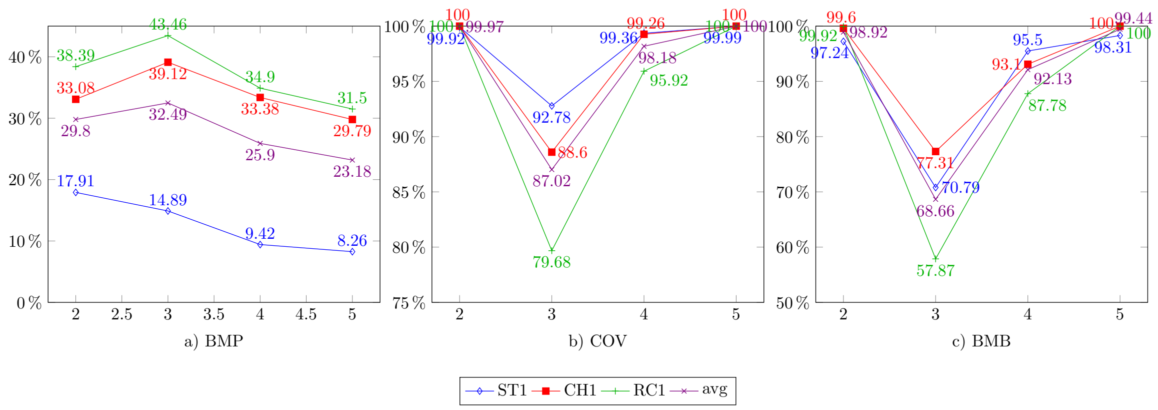

Figure 4: Values of quality metrics ((a) BMP, (b) COV, (c) BMB) obtained for diffrent data sets (ST_1, CH_1 and RC_1) and average values (AVG)

of using S_1, S_2, S_3 and S_4 within the limit of available cameras.

Results show that for every tested data set values of BMP was lower when 5 cameras were used instead of 2 ones. This is advantageous as lower BMP implies that fewer number of errors occurred in a disparity map. Results also showed that increasing the number of cameras does not always leads to lower values of BMP. In particular for data sets CH_1 and RC_1 adding a third camera to a two camera set caused a decrease of the disparity map quality estimated by BMP. It is mainly caused by the features of test data and the BP-Layers algorithm. The algorithm provides relatively large areas with same values of disparities even in case of areas for which it is impossible to obtain a disparity. This applies to all 4 considered stereo cameras from the EBCA set. In previous experiments presented in [Kac17c] it was already noticed that adding a third camera to a stereo camera does not lead to high improvement of results. However, if EBCA consists of at least four cameras the improvement is significant.

Experiments presented in this paper showed a similar relation. Increasing the number of cameras to 4 always causes that results are better than in case of using two cameras. Figure 4 also show average results calculated for data sets ST_1, CH_1 and RC_1. This chart show that on average EBCA with 5 cameras did not contain 22.18% of errors which were present in the results of using a single stereo camera.

Experiments also showed that the coverage level of disparity maps generated by BP Layers is over 99.97% as presented in 4(b). This means that the algorithm does not set values of disparity to unknown even is input images do not make it possible to appropriately acquire disparities. As a consequence the BMB metric presented in 4(c) is equal to over 98.92% for results obtained on a single stereo camera used with BP Layers as the algorithm provides incorrect values for all the background area. Number of errors in the background was reduced for all data sets when EEMM was used with three cameras. Instead of including in disparity maps incorrect values of disparities EEMM executed with three cameras caused that disparities in some areas were set to values indicating that disparities are unknown. Because of that the COV metric also became lower. Increasing number of cameras to four and five caused that values of BMB and the coverage level became almost as high as in case of using two cameras.

Experiments were also performed in order to verify whether there are stereo cameras in the EBCA set which produce better results than other cameras. Table 1 shows values of BMP obtained for different data sets with regard to the stereo camera which was used. Results show that for every data set using a different stereo camera led to obtaining the best results in terms of BMP. Camera S_2 which is the one consisting of an upper side camera generated both the best results in case of the ST_1 data set and the worst results for RC_1. It can be noticed that the S_4 camera had the worst performance. A possible cause is such that lower side camera included in S_4 is differently illuminated than other side cameras. The source of light which is the sun in open field is always above EBCA. Therefore, it might influence the measurement. However, this observation requires more investigation. Moreover, as presented in [Kac19] removing lower side camera can also be advantageous in case of mounting EBCA on a robotic arm.

Table 1: Values of BMP for different stereo cameras included in EBCA

Camera	ST_1	CH_1	RC_1
S_1 (right)	16.15%	21.75%	28.34%
S_2 (up)	7.81%	37.22%	56.95%
S_3 (left)	11.11%	25.55%	20.81%
S_4 (down)	36.58%	47.81%	47.47%

6 SUMMARY

The greatest benefit of using BP Layers with EBCA is such that on average 22.18% of errors in disparities measured with BMP are eliminated when five cameras were used instead of two ones. The BP Layers algorithm is not the one which is at the top of KITTI or Middlebury rankings. However, BP Layers has a very important features which makes this algorithm particularly important. First, it is an algorithm for which authors provided a source code. Thus, it is possible to verify its quality and results unlike most of other algorithms included in rankings of stereo matching algorithms. Second important feature is such that it is an algorithm based on CNN which has a very high speed as for such a kind of algorithm. Many stereo matching algorithms which takes advantage of CNN requires a large amount of computing and relatively a lot of time to generate results. In real application such as using the algorithm with an autonomous robot is it crucial to obtain results in real time. In KITTI Vision Benchmark presents execution times of algorithm. BP Layers runs KITTI test data in 0.39 s.

The disadvantage of using EBCA lies in the necessity to use a greater number of cameras than in case of a stereo camera. Another limitation of the research presented in this paper is such that BP Layers is an algorithm which requires using convolutional neural network. Therefore, in case of applying EBCA with this algorithm to a real autonomous robot it is necessary to equip the robot with a computer that have sufficient computational power and appropriate graphic card required by BP Layers. Using small single-board computers will not be enough. Another issue related to using EBCA in real environment is such that it was not tested under harsh weather conditions such as heavy rain.

Applying BP Layers to EBCA with the use of the EEMM method causes the increase in the execution time of matching. When 5 cameras are used BP Layers needs to be executed four times because it needs to process four pairs of images from stereo cameras S_i included in EBCA. As far as computational complexity is concerned is does not cause any change in computational complexity even though it increase the execution time four times. The merging phase consists of comparing values for every point of four disparity maps when four of them are being merged. Therefore the computational complexity of this process is linear with regard to the number of points in the image. This complexity is not higher than a complexity of stereo matching algorithm because such an algorithm also needs to process every point of input images. Therefore, computational complexity of the EBCA approach and using a single stereo camera is the same. Nevertheless processing image pairs from different stereo cameras included in EBCA can be performed independently from each other. Each pair can be processed on a different processor or different core of a processor. Making calculations parallel will cause that results from EBCA will be obtained nearly in the same time as results based on only a pair of images. The increase in time will only be caused by the necessity to run the EEMM merging method which does not require significant computation power. Taking into account that the quality of this results will be higher it is an acceptable cost.

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