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(54) **METHOD AND DEVICE FOR 3D OBJECT DETECTION**

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CPC ***G06V 10/82*** (2022.01); ***G06T 7/593*** (2017.01); ***G06T 7/73*** (2017.01); ***G06V 10/42*** (2022.01);
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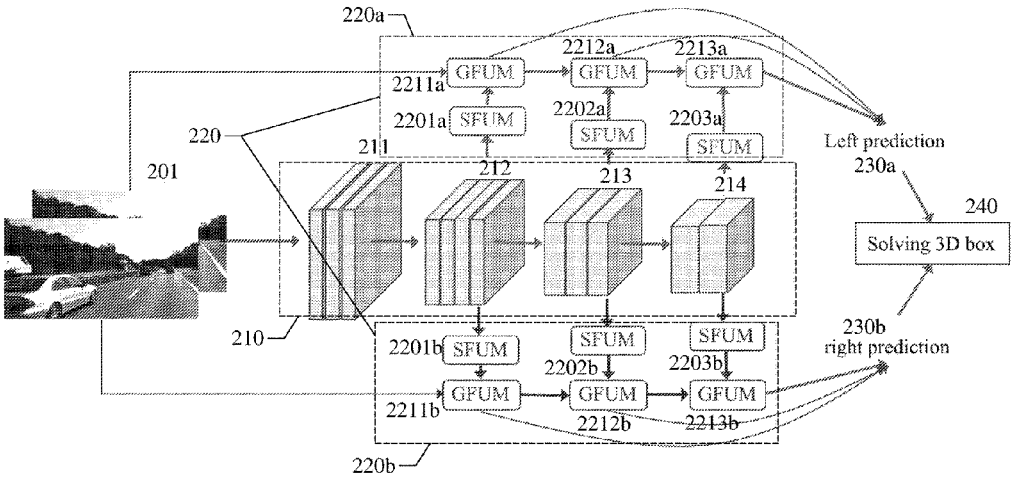
(57) **ABSTRACT**

A method and device for 3D object detection. The method comprises the steps of: generating one or more fused images (**201**) based on a pair of images(**530**), the pair of images (**530**) including a left view image(**101**,**710***a*) and a right view image(**102**,**710***b*); extracting one or more fused features from the fused images(**201**) by a single backbone network(**210**) of a share network with feature unmixing (SNFU,**540**); unmixing the fused features to a left view-aware feature and a right view-aware feature by a feature unmixing sub-network(**220**) of the SNFU(**540**); predicting the 3D object based on the left view-aware feature and the right view-aware feature; and determining spatial features of the predicted 3D object. The proposed method and device can reduce the computation complexity to the level of that in monocular based 2D object detection so as to improve the computation efficiency while keeping high precision. In addition, the PCNet network for depth estimation can achieve the competitive performance on accuracy and high
(Continued)



speed simultaneously when predicting the depth of the 3D object.

22 Claims, 12 Drawing Sheets

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G06V 10/42	(2022.01)
G06V 10/77	(2022.01)
G06V 10/80	(2022.01)
G06V 20/64	(2022.01)

(52) **U.S. Cl.**

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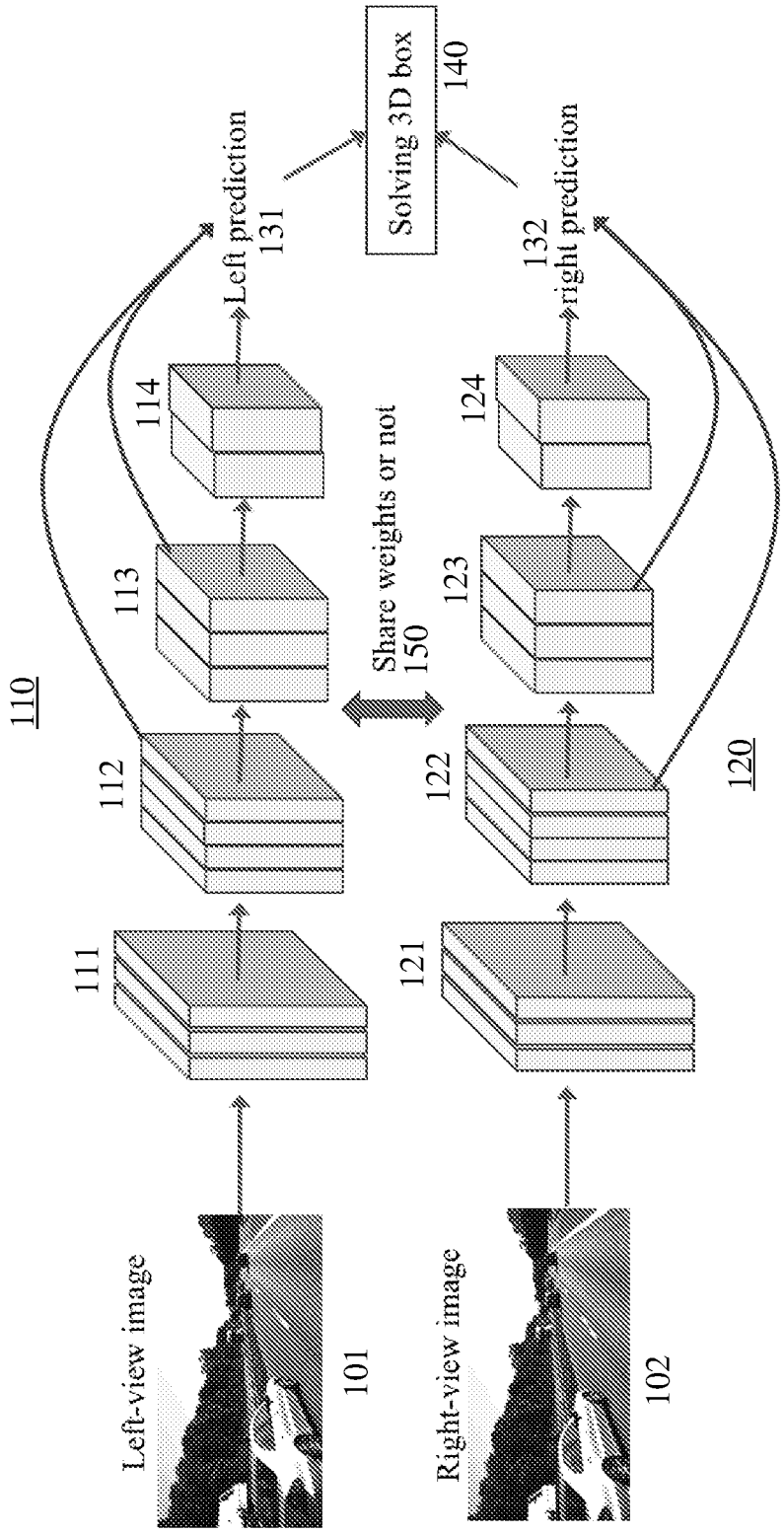
Left-view image
101
Right-view image
102
111
112
113
114
121
122
123
124
110
120
Share weights or not
150
Left prediction
131
right prediction
132
Solving 3D box
140

Figure 1

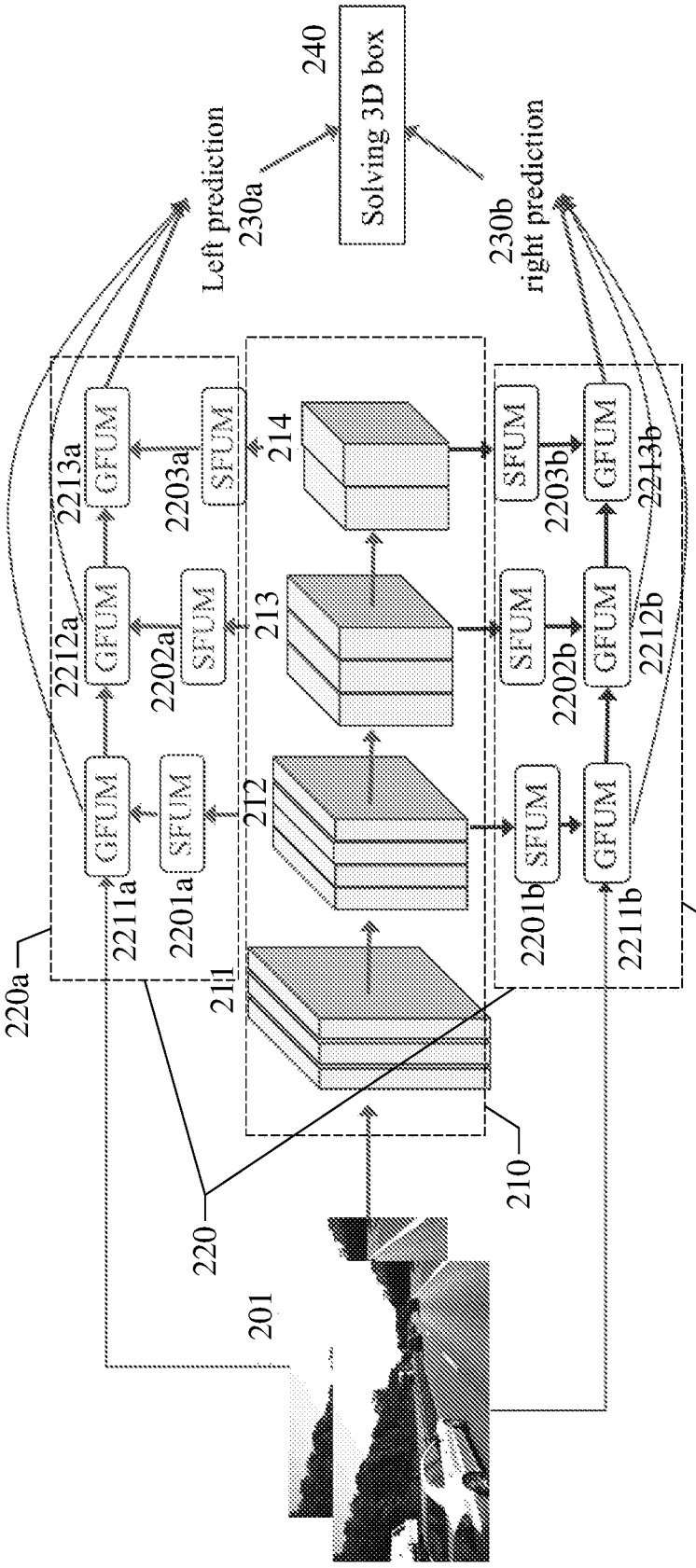
240
Solving 3D box
Left prediction
230a
230b
right prediction
2213a
GFUM
2203a
SFUM
214
SFUM
2203b
GFUM
2213b
2212a
GFUM
2202a
SFUM
213
SFUM
2202b
GFUM
2212b
2211a
GFUM
2201a
SFUM
212
2201b
SFUM
GFUM
2211b
220a
211
210
220
201
220b

Figure 2

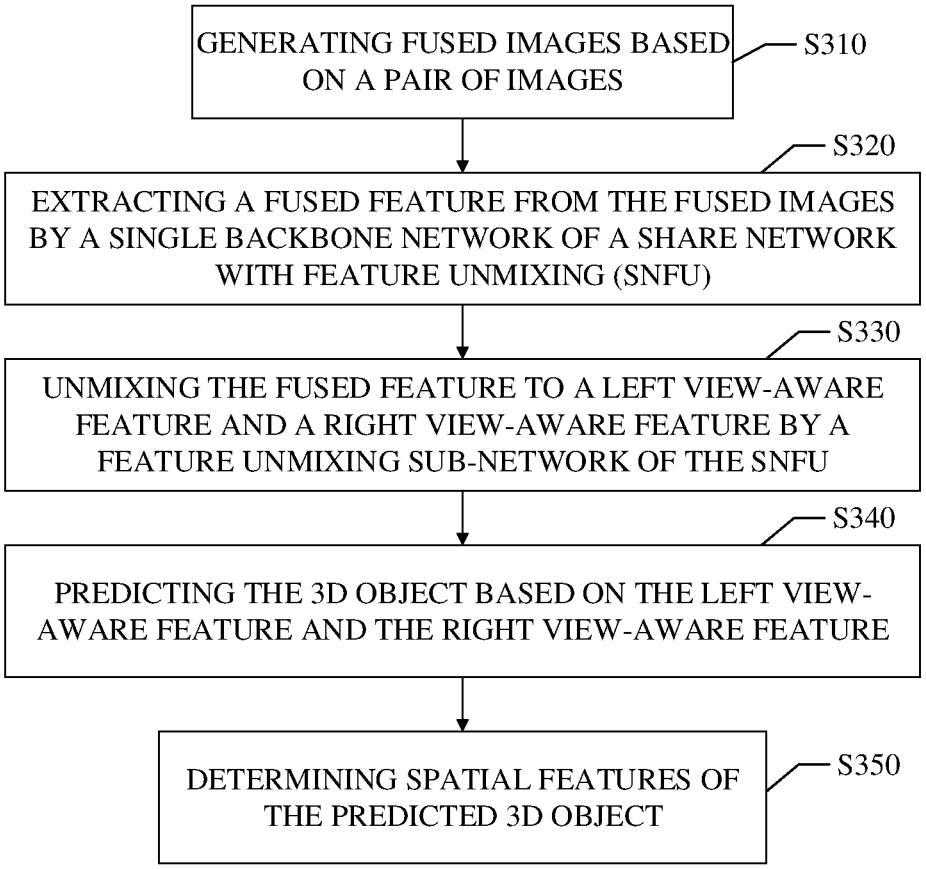
GENERATING FUSED IMAGES BASED ON A PAIR OF IMAGES
S310
EXTRACTING A FUSED FEATURE FROM THE FUSED IMAGES BY A SINGLE BACKBONE NETWORK OF A SHARE NETWORK WITH FEATURE UNMIXING (SNFU)
S320
UNMIXING THE FUSED FEATURE TO A LEFT VIEW-AWARE FEATURE AND A RIGHT VIEW-AWARE FEATURE BY A FEATURE UNMIXING SUB-NETWORK OF THE SNFU
S330
PREDICTING THE 3D OBJECT BASED ON THE LEFT VIEW-AWARE FEATURE AND THE RIGHT VIEW-AWARE FEATURE
S340
DETERMINING SPATIAL FEATURES OF THE PREDICTED 3D OBJECT
S350

Figure 3

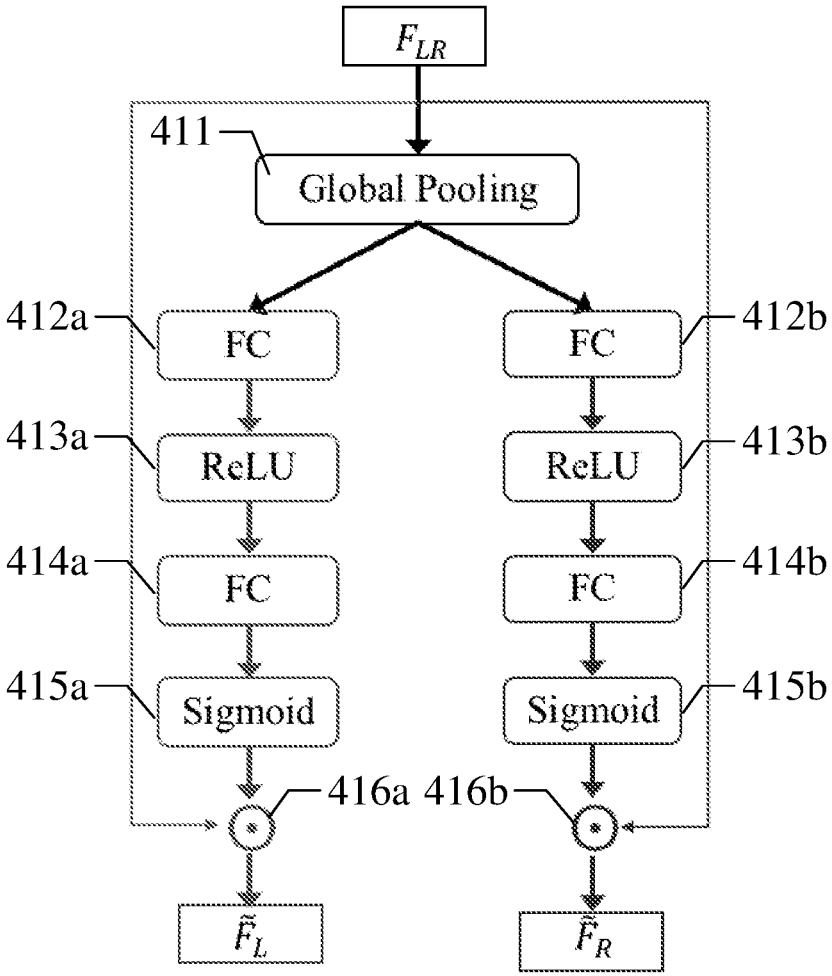
F_{LR}
411
Global Pooling
412a
FC
412b
FC
413a
ReLU
413b
ReLU
414a
FC
414b
FC
415a
Sigmoid
415b
Sigmoid
416a 416b
$\tilde{F}_L$
$\tilde{F}_R$

Figure 4A

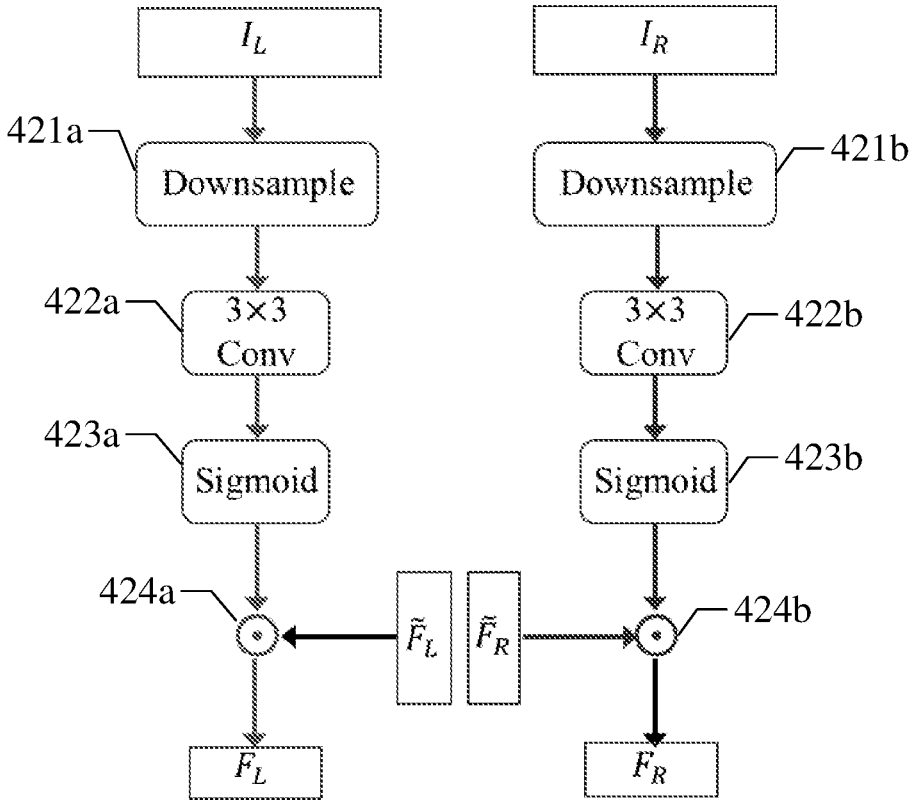
I_L
I_R
421a
Downsample
421b
Downsample
422a
3×3 Conv
422b
3×3 Conv
423a
Sigmoid
423b
Sigmoid
424a
$\tilde{F}_L$
$\tilde{F}_R$
424b
F_L
F_R

Figure 4B

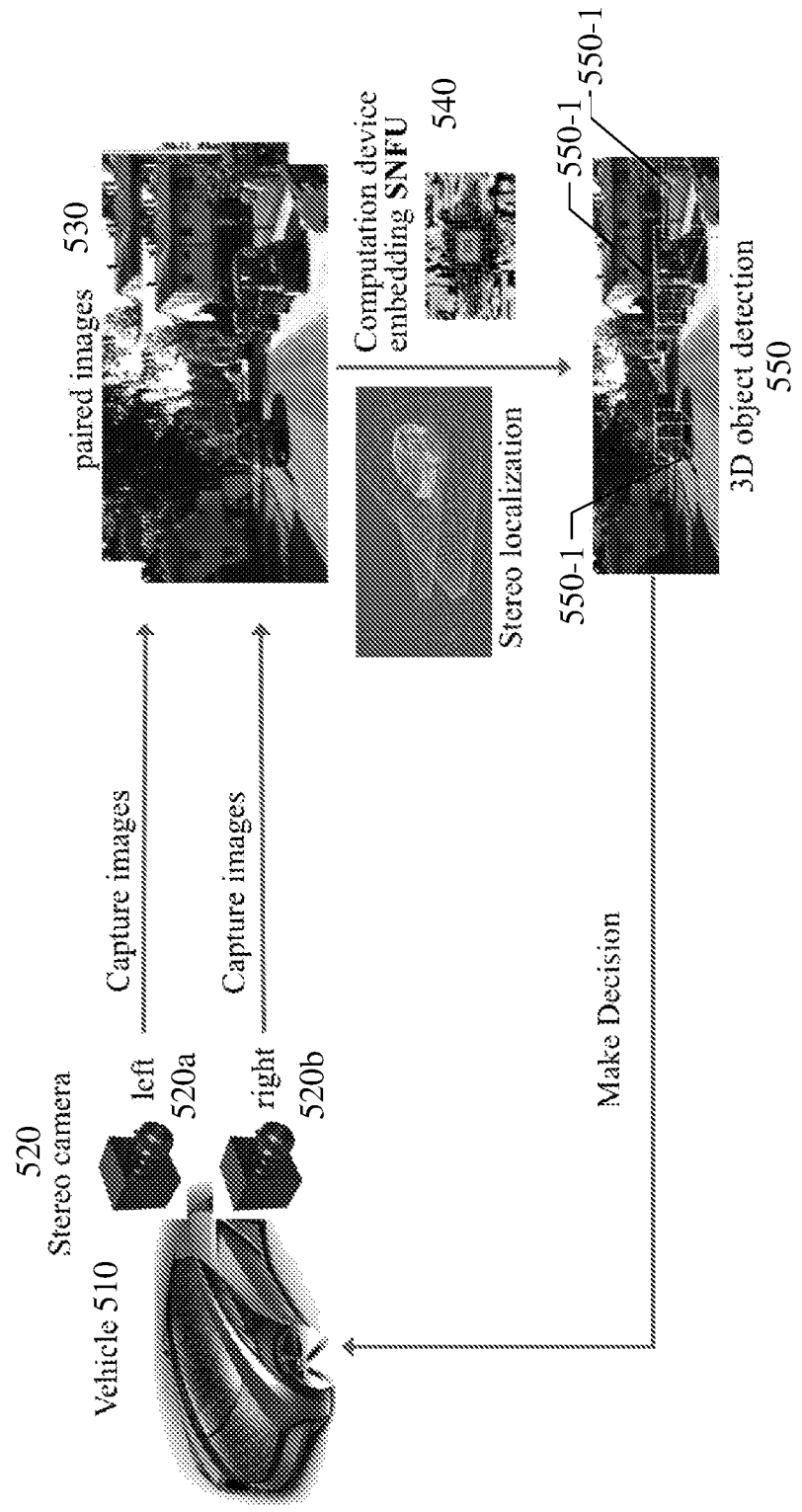
520
Stereo camera
Vehicle 510
left
520a
right
520b
Capture images
Capture images
paired images
530
Computation device
embedding SNFU
540
Stereo localization
550-1
550-1
550-1
3D object detection
550
Make Decision

Figure 5

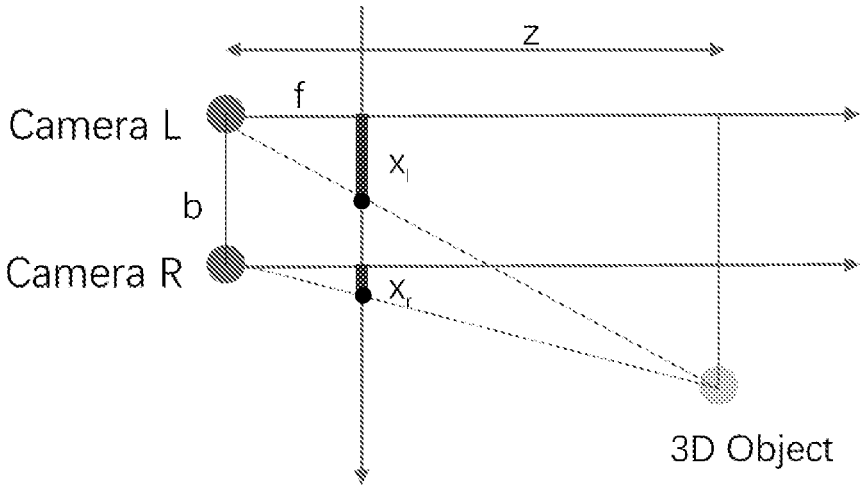

Figure 6

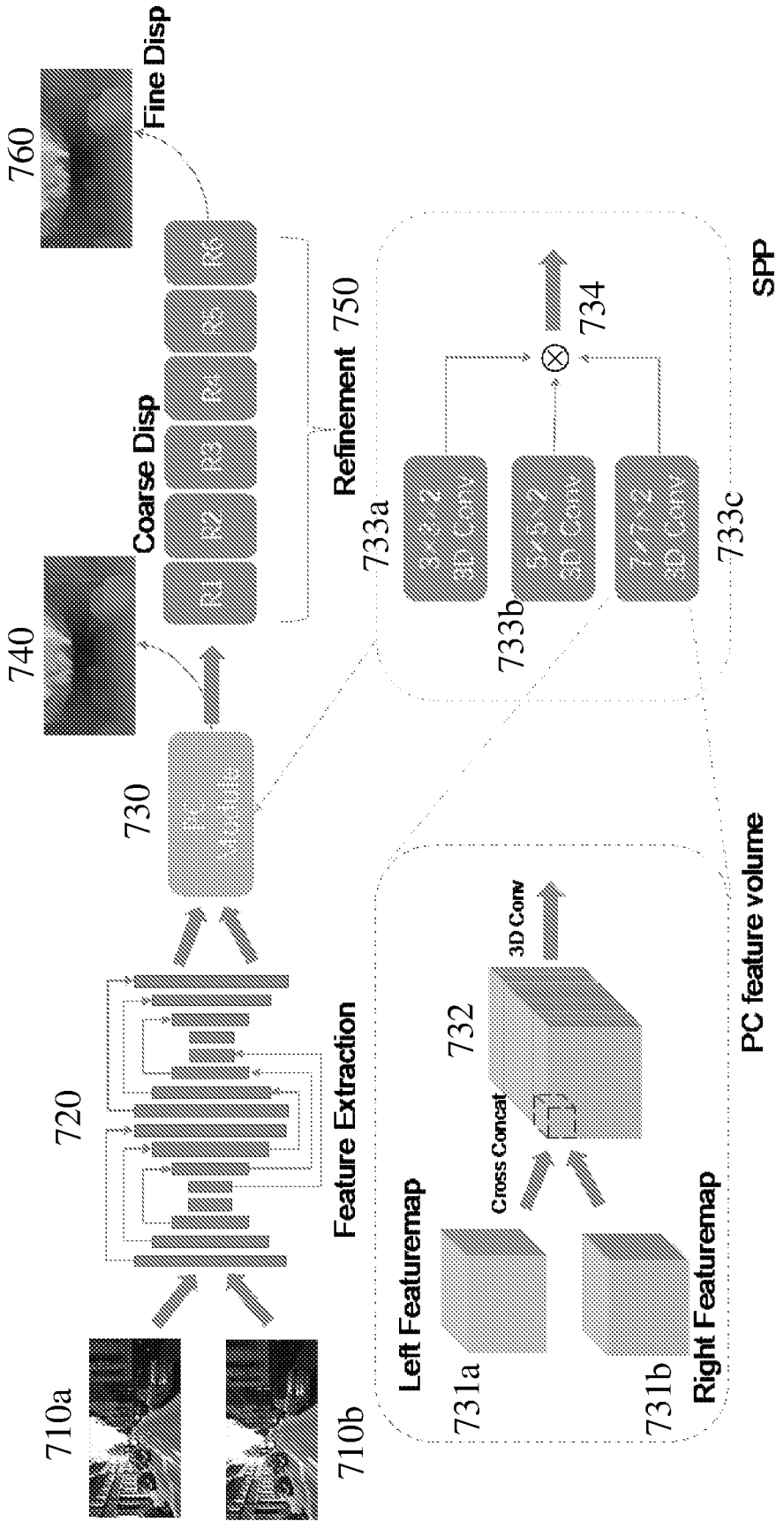
760
Fine Disp
740
Coarse Disp
R1
R2
R3
R4
R5
Refinement 750
730
720
Feature Extraction
710a
710b
Left Featuremap
731a
Cross Concat
732
3D Conv
731b
Right Featuremap
PC feature volume
733a
3D Conv
733b
3D Conv
733c
3D Conv
734
SPP

Figure 7

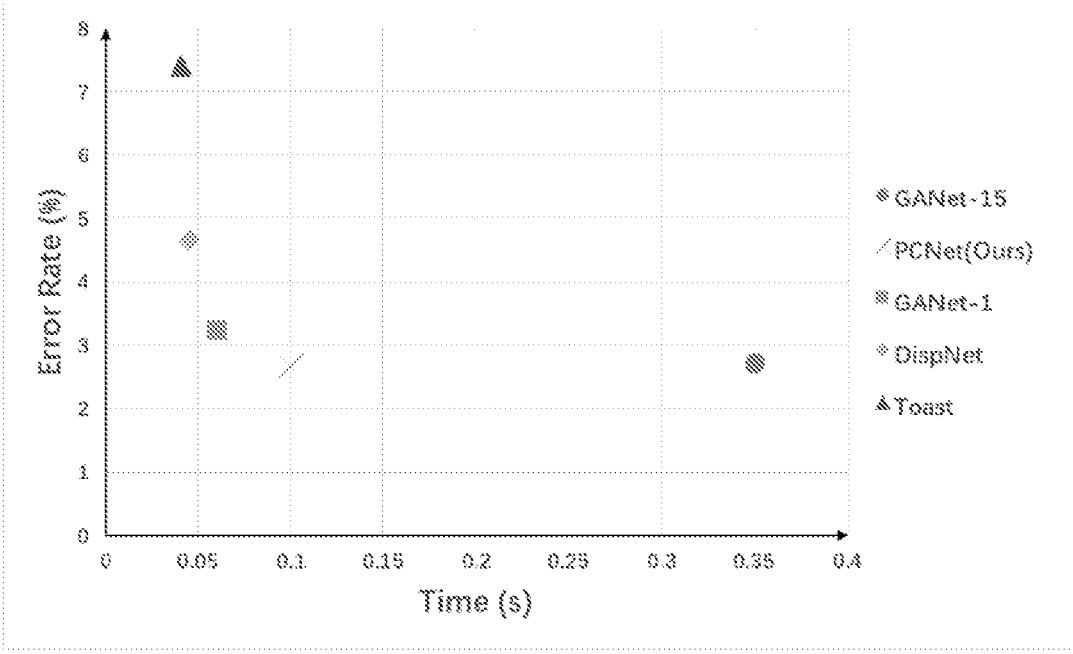
Error Rate (%)
Time (s)
0
1
2
3
4
5
6
7
8
0
0.05
0.1
0.15
0.2
0.25
0.3
0.35
0.4
GANet-15
PCNet(Ours)
GANet-1
DispNet
Toast

Figure 8

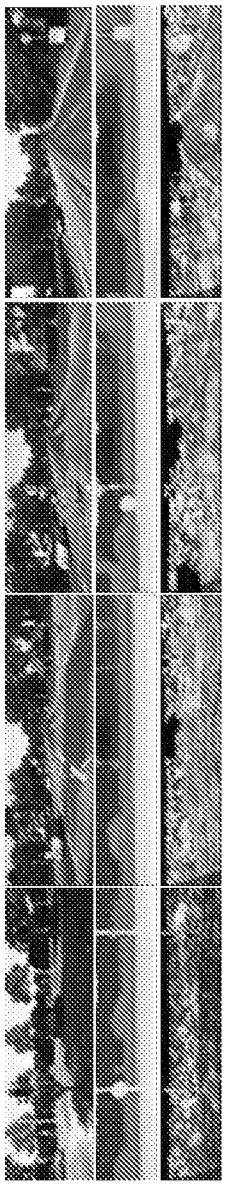

Figure 9

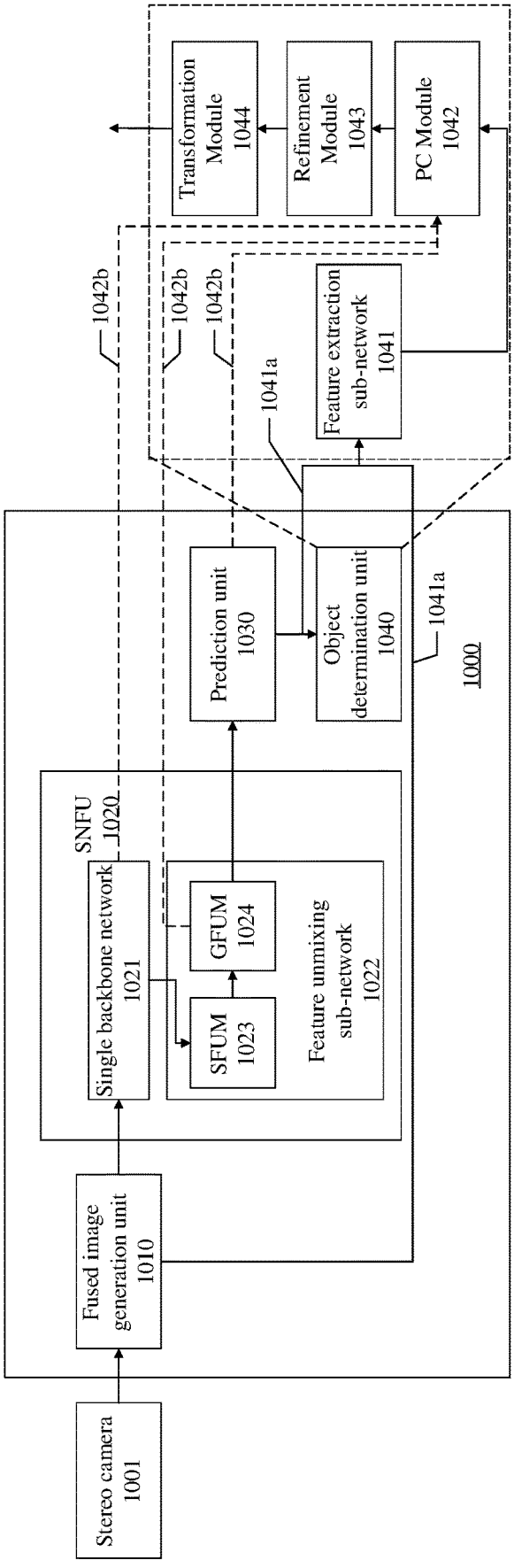
Stereo camera 1001
Fused image generation unit 1010
SNFU 1020
Single backbone network 1021
Feature unmixing sub-network 1022
SFUM 1023
GFUM 1024
Prediction unit 1030
Object determination unit 1040
1041a
1000
Feature extraction sub-network 1041
1041a
1042b
1042b
1042b
PC Module 1042
Refinement Module 1043
Transformation Module 1044

Figure 10

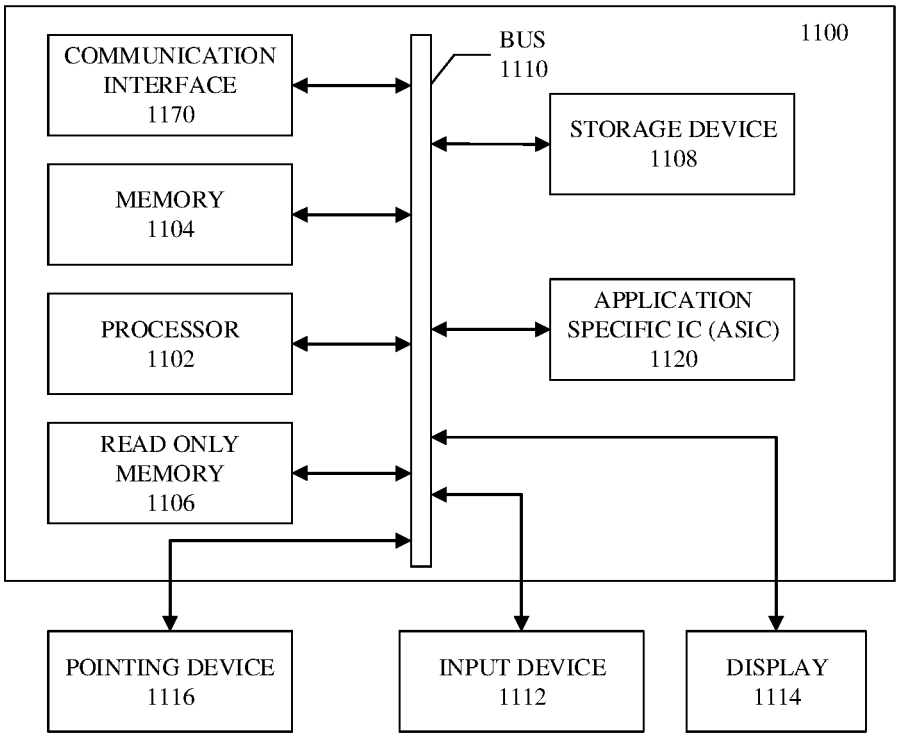
1100
BUS
1110
COMMUNICATION INTERFACE
1170
STORAGE DEVICE
1108
MEMORY
1104
PROCESSOR
1102
APPLICATION SPECIFIC IC (ASIC)
1120
READ ONLY MEMORY
1106
POINTING DEVICE
1116
INPUT DEVICE
1112
DISPLAY
1114

Figure 11

METHOD AND DEVICE FOR 3D OBJECT DETECTION

RELATED APPLICATION

This application was originally filed as PCT Application No. PCT/CN2020/086439, filed on Apr. 23, 2020, which is incorporated herein by reference in its entirety.

FIELD OF THE INVENTION

The present disclosure generally relates to image processing, and more specifically, to a method and device for three-dimension (3D) object detection.

BACKGROUND

3D object detection is an important computer vision task in various applications such as Human-Machine Interaction, Security Surveillance, and Advanced Driver Assistant Systems (ADAS). Different from general monocular based 2D object detection in which only 2D information (box coordinates) in the image are provided, 3D objects are detected to provide detailed 3D localization information containing a set of object size, orientation, and depth, or a set of height, width, and depth in real-world scenes. Depth estimation is a classical computer vision problem which describes the distance between observation point and objects. Especially in the situation of Autonomous Driving, it is significant to detect the 3D object precisely, especially get the information of depth can avoid the accident of autonomous vehicle crashing into car and pedestrian. Meanwhile, the depth information is also helpful in detection and segmentation tasks. So the accuracy and the speed are two important points which we concern the most.

To implement 3D object detection, LiDAR (Light Detection and Ranging) or stereo cameras can be adopted. Depth information obtained by LiDAR is super-accurate. In consideration that LiDAR is much more expensive than stereo cameras, binocular 3D object detection based on stereo camera is much promising in practical applications.

Deep learning become one of the most popular technology which can be used in Computer Vison (CV) and Natural Language Processing (NLP). In the past few years with the development of deep learning, the performance of self-driving and robotics has improved a lot on both accuracy and speed. Deep learning is also used in 3D object detection. In Computer Vision, the architecture called Convolutional Neural Network (CNN) which is based on deep learning is used widely.

However, considering a pair of images input for 3D object detection, the computation devices need to process two images for once 3D prediction, which doubles the computation complexity and amount when comparing with monocular based 2D object detection by using single image.

In addition, although the price of stereo camera is satisfied in application, classical stereo depth estimation methods are not satisfied on both accuracy and efficiency. Existing deep learning stereo depth estimation methods achieve good accuracy but low efficiency for involving to many 3D convolutional layers which cost a lot of computation.

Thus, there is a need for improving the method and device for 3D object detection.

SOME EXAMPLE EMBODIMENTS

To overcome the problem described above, and to overcome the limitations that will be apparent upon reading and understanding the prior arts, the embodiments of present disclosure provide a method and device for 3D object detection.

According to the first aspect of the disclosure, a method for 3D object detection is presented. The method comprises the steps of: generating one or more fused images based on a pair of images, the pair of images including a left view image and a right view image; extracting one or more fused features from the fused images by a single backbone network of a share network with feature unmixing (SNFU); unmixing the fused features to a left view-aware feature and a right view-aware feature by a feature unmixing sub-network of the SNFU; predicting the 3D object based on the left view-aware feature and the right view-aware feature; and determining spatial features of the predicted 3D object.

According to an exemplary embodiment, the pair of images is obtained by a stereo camera.

According to an exemplary embodiment, generating one or more fused images based on the pair of images further comprises: generating one or more fused images by concatenating the channels of the left and right view images along respective channel dimensions.

According to an exemplary embodiment, the backbone network comprises an input convolutional block and one or more downsampling convolutional blocks which are connected in sequence, the input convolutional block being configured to receive the fused images, the downsampling convolutional blocks, each of which comprises at least one convolutional layer, being configured to generate one or more fused features comprising image features with different spatial sizes.

According to an exemplary embodiment, unmixing the fused feature to the left view-aware feature and the right view-aware feature further comprises: generating left initial view-aware features and right initial view-aware features based on the fused features by a self-feature unmixing module (SFUM) of the feature unmixing sub-network; and generating left view-aware features and right view-aware features based on the left initial left view-aware features and the right initial view-aware features by a guided-feature unmixing module (GFUM) of the feature unmixing sub-network.

According to an exemplary embodiment, generating the left initial view-aware features and the right initial view-aware features based on the fused features further comprises: extracting global size image features from the fused features by a global average pooling operation and full convolution operations; and generating the left initial view-aware features and the right initial view-aware features by reweighting different channels of the global size image features.

According to an exemplary embodiment, the different channels of the global size image features are reweighted by element-wise multiplying the global size image features by the fused features, respectively.

According to an exemplary embodiment, generating the left view-aware features and the right view-aware features based on the left initial left view-aware features and the right initial view-aware features further comprises: downsampling the left and right view images according to the spatial sizes of the image features of the fused features, respectively; generating spatial position information for the 3D object in the left and right view images respectively; and generating the left and right view-aware features, based on the spatial position information for the 3D object in the left

view image and the right view image, and the left initial view-aware features and the right initial view-aware features, respectively.

According to an exemplary embodiment, the left view-aware features are generated by element-wise multiplying the spatial position information for the 3D object in the left view image by the left view image, and the right view-aware features are generated by element-wise multiplying the spatial position information for the 3D object in the right view image by the right view image.

According to an exemplary embodiment, at least one of the backbone network and the feature unmixing sub-network is convolution neutral network.

According to an exemplary embodiment, the backbone network is selected from the group consisted of ResNet, VGG, DenseNet, and search-based network.

According to an exemplary embodiment, the SNFU is trained based on a training data set prior to be used for extracting the fused features from the fused images and/or for unmixing the fused features to a left view-aware feature and a right view-aware feature.

According to an exemplary embodiment, the spatial features of the 3D object comprise a height, a width, and a depth of the 3D object, determining spatial features of the predicted 3D object further comprises: determining the depth of the 3D object based on the height and the width of the 3D object predicted in the left and right view images, by a paired channel cost volume network (PCNet).

According to an exemplary embodiment, determining the depth of the 3D object based on the height and the width of the 3D object predicted in the left and right view images further comprises: extracting feature maps of the left and right view images from the left and right view images, by a feature extraction sub-network of the PCNet; generating a coarse disparity based on the channels of the feature maps of the left and right view images, by a paired channel module of the PCNet; refining the coarse disparity to a fine disparity; and transforming the fine disparity to the depth of the 3D object.

According to an exemplary embodiment, determining the depth of the 3D object based on the height and the width of the 3D object predicted in the left and right view images further comprises: generating a coarse disparity based on the channels of the feature maps of the left and right view images, by a paired channel module of the PCNet, wherein the feature maps of the left and right view images are the fused features extracted by the backbone network or the left and right view-aware features unmixed by the feature unmixing sub-network, respectively; refining the coarse disparity to a fine disparity; and transforming the fine disparity to the depth of the 3D object.

According to an exemplary embodiment, the paired channel module has a spatial pyramid pooling structure with three parallel paired channel feature volumes and three paired channel filters with different spatial sizes, generating a coarse disparity based on the channels of the feature maps of the left and right view images further comprises: generating the three parallel paired channel feature volumes by concatenating the channels of the feature map of the left view image and the corresponding channels of feature map of the right view images along channel dimensions of height and width of the predicted 3D object and color of the left and right view images respectively; and extracting the coarse disparity from the three parallel paired channel features volumes by respective paired channel filters.

According to an exemplary embodiment, the feature extraction sub-network comprises two stacked hourglass structure with dense connection configured to extract the feature maps of the left and right view images from the left and right view images.

According to an exemplary embodiment, the coarse disparity is refined to a fine disparity by at least one stacked residual block constructed by 2D convolution layers.

According to an exemplary embodiment, the PCNet is trained based on a training data set prior to be used for determining the disparity of the 3D object based on the height and the width of the 3D object predicted in the left and right view images.

According to an exemplary embodiment, the PCNet is a convolution neutral network.

According to the second aspect of the disclosure, a device for 3D object detection is presented. The device comprises: a fused image generation unit configured to generate one or more fused images based on a pair of images, the pair of images including a left view image and a right view image; a share network with feature unmixing (SNFU), the SNFU comprising a single backbone network configured to extract one or more fused features from the pair of images and a feature unmixing sub-network configured to unmix the fused features to a left view-aware feature and a right view-aware feature; a prediction unit configured to predict the 3D object based on the left view-aware feature and the right view-aware feature; and an object determination unit configured to determine spatial features of the predicted 3D object.

According to the third aspect of the disclosure, a non-transitory computer-readable storage medium is presented. The non-transitory computer-readable storage medium stores instructions which, when executed by one or more processor, cause the processor to perform the method above-mentioned in the first aspect of the disclosure.

The method and device by using the Share Network of SNFU to implement efficient 3D object detection reduces the computation complexity to the level of that in monocular based 2D object detection, so as to improve the computation efficiency while keeping high precision. Even for multi-view system with multiple cameras, the proposed method and device can implement 3D object detection as efficient as monocular based 2D object detection. In addition, the PCNet network for depth estimation for 3D object can achieve both the competitive performance on accuracy and high speed when predicting the depth of 3D object, so as to achieve better performance in the autonomous driving system.

Still other aspects, features, and advantages of the disclosure are readily apparent from the following detailed description, simply by illustrating a number of particular embodiments and implementations, including the best mode contemplated for carrying out the disclosure. The disclosure is also capable of other and different embodiments, and its several details may be modified in various obvious respects, all without departing from the spirit and scope of the disclosure. Accordingly, the drawings and description are to be regarded as illustrative in nature, and not as restrictive.

BRIEF DESCRIPTION OF THE DRAWINGS

The exemplary embodiments of the disclosure are illustrated by way of example, and not by way of limitation, in the figures of the accompanying drawings:

FIG. **1** illustrates a diagram of an exemplary framework of binocular-based TNet method for 3D object detection;

FIG. **2** illustrates a diagram of a framework of binocular-based SNFU method for 3D object detection according to an exemplary embodiment of present disclosure;

FIG. **3** illustrates a flow chart of the method based on a share network of SNFU for 3D object detection according to an exemplary embodiment of present disclosure;

FIG. **4**A illustrates the structure of a self-feature unmixing module (SFUM) of the feature unmixing sub-network of the SNFU according to an exemplary embodiment of present disclosure;

FIG. **4**B illustrates the structure of a guided-feature unmixing module (GFUM) of the feature unmixing sub-network of the SNFU according to an exemplary embodiment of present disclosure;

FIG. **5** illustrates the application for autonomous driving by the 3D object detection via the share network of SNFU according to an exemplary embodiment of present disclosure;

FIG. **6** illustrates the fundamental of stereo depth estimation according to an exemplary embodiment of present disclosure;

FIG. **7** illustrates a diagram of a framework of the paired channel cost volume network (PCNet) according to an exemplary embodiment of present disclosure;

FIG. **8** illustrates the result of comparison between PCNet and other method according to an exemplary embodiment of present disclosure;

FIG. **9** illustrates the predicted depth of PCNet on KITTI 2015 dataset according to an exemplary embodiment of present disclosure;

FIG. **10** illustrates a block diagram of a device for 3D object detection according to an exemplary embodiment of present disclosure; and

FIG. **11** illustrates a computer system upon which an exemplary embodiment of present disclosure can be implemented.

DETAILED DESCRIPTION OF THE INVENTION

The present disclosure includes any novel feature or combination of features disclosed herein either explicitly or any generalization thereof. Various modifications and adaptations to the foregoing exemplary embodiments of this disclosure may become apparent to those skilled in the relevant arts in view of the foregoing description, when read in conjunction with the accompanying drawings. However, any and all modifications will still fall within the scope of the non-limiting and exemplary embodiments of this disclosure.

There are some monocular based 3D object detection methods which directly estimates the 3D information of the objects from a single-view image. However, single-view image only contains 2D information which limits the 3D performance seriously. Using LiDAR is much more expensive in practice. Different from monocular and LiDAR based methods, binocular based methods detect objects using paired images which helps recover the stereo information of practical scenes.

In order to implement 3D object detection by taking two networks each of which is responsible for processing a single-view image, some researchers propose a Stereo-RCNN or a 3DOP neutral network method. Other researchers also propose Pseudo-Lidar based methods to use a two-stream network to generate pseudo LiDAR points and use a LiDAR-based method to predict 3D information of objects. In the two-stream network solutions, a TLNet that adopts two networks to process the paired images separately is an optional approach.

FIG. **1** illustrates a typical framework of binocular-based methods, called TNet, using two networks for 3D object detection. The TNet method is a binocular based 3D object detection method with deep Convolutional Neural Networks (CNN), where a pair of images, i.e., the left-view image **101** and the right-view image **102** are inputted to two networks **110**, **120** (also called as two-stream network) for feature extraction and result prediction. The network **110** comprises four convolution blocks of **111**, **112**, **113**, and **114**, and the network **120** comprises another four convolution blocks of **121**, **122**, **123**, and **124**. The output of network **110** is fed to left prediction **131** to obtain the predicted object in left view. The prediction contains results for keypoint regression, 2D box coordinates, orientation which are important for solving 3D information. This processing is carried out for network **120** similarly. The predicted object by left and right predictions are used together to solve the 3D box **140** (i.e. 3D bounding box) in the binocular images. Although the two network **110** and **120** may share weights **150**, it is noted that each network is responsible for feature extraction of a single-view image. That is, the computation complexity is doubled for paired inputs, which limits the application of 3D object detection in real-time scenarios. Especially, in multi-view system, the computation consumption will be doubled and redoubled. However, in practical applications like autonomous driving, fast real-time object detection and strategy adjusting are needed. Based on the observation that in these paired images the appearance and pixel values of the same object are similar, using two networks to process two images separately is time-consuming and non-optimal.

To meet the practical demands, the exemplary embodiment of present disclosure proposes a Share Network with Feature Unmixing (called as SNFU) method as an image segmentation approach for binocular based 3D object detection, which helps to reduce the computation complexity dramatically while keeping the detection precision and improving the detection efficiency. The SNFU processes paired images and embeds with the feature unmixing method to generate separate-view features for subsequent prediction. In SNFU, for a pair of images, a single share backbone network is used to extract the one or more general fused features. Then a light-weight feature unmixing sub-network by embedding a self-feature unmixing module (called as SFUM) and a guided-feature unmixing module (called as GFUM) separates the one or more fused features to left-view and right-view (view-aware) features. Subsequently, these view-aware features are used for 3D prediction. Because only one share backbone network instead of two networks is used for feature extraction, about 50% computation complexity is cut down in comparison to TNet-based solutions. SNFU method and device can reduce the redundant computation for similar features while the unmixing modules help to separate multi-view features, such that the proposed solution can improve the detection efficiency dramatically and keeping detection precision, which is much suitable for practical applications.

The 3D object detection process according to an exemplary embodiment of the disclosure is introduced in details below with reference to FIGS. **2** and FIG. **3**, where FIG. **2** illustrates the diagram of a framework of binocular-based SNFU method and FIG. **3** is the exemplary flow chart of the SNFU method.

The share network of SNFU has a single backbone network **210** and a light-weighted feature unmixing sub-network **220** including an upper part **220***a* and a lower part **220***b*. The feature unmixing sub-network **220** further comprises a self-feature unmixing module (SFUM) **2201***a*,

2202*a*, **2203***a*, **2201***b*, **2202***b*, and **2203***b*, and a guided-feature unmixing module (GFUM) **2211***a*, **2212***a*, **2213***a*, **2211***b*, **2212***b*, and **2213***b*.

Firstly, a pair of images including a left view image and a right view image are obtained and used for generating one or more fused images as the input of the share network of SNFU, in step **S310**. The pair of binocular based images can be obtained by a stereo camera, such as paired cameras or multi-view cameras, in which the left view image is obtained by the left camera and the right view image is obtained by the right camera.

The obtained images are 2D images including 3D information of objects. The 3D information is represented by the RGB color channels. The left and right view images have total six RGB color channels (can also be called as channel dimensions), i.e., Red, Green, and Blue color channels of the left one, and Red, Green, and Blue color channels of the right one. These six channels include enough 3D information required to solving the spatial features of the 3D object, such as the Height channel, Width channel, and Depth channel. In addition, the Depth channel spatial feature can also be transferred to a Disparity channel spatial feature.

Based on the observation that a 3D object in the left-view and right-view images has the similar appearance and pixel values, using one single backbone network is capable of extracting abundant features. One backbone network in the share network of SNFU according to the exemplary embodiment is used for feature extraction for a paired of images as:

$$F_{LR}=\mathcal{T}(I_L,I_R;W), \tag{1}$$

where F_{LR} represents the one or more extracted fused features, I_L represents the left view image, I_R represents the right view image, W represents the learned parameters of the single backbone network $\mathcal{T}(.)$ of SNFU.

In comparison to the two-stream network, the channels of images are fused to generate one or more fused images **201** so as to be processed by the share network of SNFU. The fused images **201**, also called stacked images, can be generated by concatenating the channels of the left and the right view images along respective channel dimensions. After the concatenation operation, the fused images **201** have the concatenated channel dimensions in form of Red color channel of the left view image, Red color channel of the right view image, Green color channel of the left view image, Green color channel of the right view image, Blue color channel of the left view image, and Blue color channel of the right view image, in sequence. Therefore, in the embodiment of present disclosure, the fused images **201** with six channel dimensions are taken as input of the share network of SNFU, which is different from the configuration that the two-stream network takes an image with three channel dimensions (RGB channels of one image). In the input convolutional block of the backbone network of SNFU, the convolutional kernels are modified with six channels instead of three. It can be easily found that the share network of SNFU can reduce about 50% computation consumption of previous methods. It is noted that each of the input convolutional block **211** and one or more downsampling convolutional blocks have at least one convolutional layer.

In step **320**, the fused features are extracted from the fused images **201** by the single backbone network **210** of the share network of SNFU. It is noted that the backbone network is selected from the group consisted of, for example, many convolution neutral networks (CNN), such as, full convolution neutral networks, such as ResNet, VGG, DenseNet, search-based network, etc.

The backbone network **210** comprise an input convolutional block **211**, and one or more downsampling convolutional blocks, such as **212**, **213**, and **214**. The input convolutional block **211** receives the input of one or more fused images **201**. The one or more downsampling convolutional blocks are configured to generate fused features based on the output of the input convolutional block **211**. Each of the downsampling convolutional blocks generates the image features with different spatial sizes. For example, the downsampling convolutional block **212** generates image features with ½ of the spatial sizes of the output images of the input convolutional block **211**, which is identical to the spatial size of the left and right view images, the downsampling convolutional block **213** generates image features with ¼ of the spatial sizes of the left and right view images, which is ½ of the spatial sizes of the output of the previous downsampling convolutional block **212**, and the downsampling convolutional block **214** generates image features with ⅛ of the spatial sizes of the left and right view images, which is ½ of the spatial sizes of the output of the previous downsampling convolutional block **213**. The smaller the spatial size is, the more global features are focused. The downsampling degrees of the downsampling convolutional blocks and/or the number of the downsampling convolutional blocks can be selected with other values according to demands. The fused features comprise all of the image features with different spatial sizes outputted by the one or more downsampling convolutional blocks **212**, **213**, and **214**, and the fused features contain both information for left and right view images.

To better describe the 3D object detection process, the exemplary backbone network **210** of SNFU is configured, for example, with three downsampling convolutional blocks. The convolutional block configuration of backbone network **210** can be adjusted to meet the practical demands, such as a configuration of one input convolutional block and two downsampling convolutional blocks, a configuration of one input convolutional block and four downsampling convolutional blocks, etc.

After the fused images generation by the single backbone network **210**, the fused features are unmixed to a left view-aware feature and a right view-aware feature by the feature unmixing sub-network **220** of the SNFU, in step **330**.

Since the one or more extracted fused features from the fused images contain both the information for the left view image and the information for the right view image, they need to be unmixed. To generate view-aware features, i.e., separate the fused features to the left view features F_L and right-view features F_R, for 3D object prediction, the fused features are unmixed as:

$$F_L,F_R=\mathcal{U}(F_{LR};W_U), \tag{2}$$

where $\mathcal{U}(;W_u)$ represents the feature unmixing operation with learnable parameters W_U of the feature unmixing sub-network **220** of SNFU. In an embodiment, the feature unmixing sub-network **220** is constructed, for example, by convolution neutral networks, such as, full convolution neutral networks. The feature unmixing sub-network **220** comprises two modules as described below.

FIG. **4**A illustrates the structure of the self-feature unmixing module (SFUM) of the feature unmixing sub-network **220** of the SNFU according to an exemplary embodiment of present disclosure. The SFUM is configured to generate left initial view-aware features and right initial view-aware features based on the fused features outputted by the single backbone network **210**.

To unmix the extracted fused features to view-aware features, the SFUM separates the channel information based on the consideration that different channels have different emphasis on different views. As shown in FIG. **4**A, SFUM first uses a global average pooling layer **411** performing the global average pooling operation $\mathcal{G}(.)$ to generate the channel response values, i.e., the global size image features. Since the fused features outputted by the downsampling convolutional blocks **212** to **214** comprise a plurality of image features with different spatial sizes, the SFUM needs to perform the global average pooling operation to each of the image features. In FIG. **2**, SFUMs **2201***a*, **2202***a*, and **2203***a*, and SFUMs **2201***b*, **2202***b*, and **2203***b* correspond to the outputs from downsampling convolutional blocks **212** to **214**, respectively, where "a" and "b" in the last character of the reference numbers identify the type of images, for example, SFUM **2201***a* performs the pooling operation to the image feature from the convolutional block **212** corresponding to the left view image, and SFUM **2201***b* performs the pooling operation to the image feature from the convolutional block **212** corresponding to the right view image, etc. Therefore, the upper part **220***a* of the feature unmixing sub-network **220** corresponds to the part for left view images, and the lower part **220***b* of the feature unmixing sub-network **220** corresponds to the part for right view images. This definition of types "a" and "b" is used to identify the left and right view images throughout the context of the description.

Then two branches are used to reweight the channel information for left view and right view images, respectively as:

$$\tilde{F}_L=\mathcal{U}_{SFUM_L}(\mathcal{G}(F_{LR});W_{SFUM_L};\odot),\tilde{F}_R=\mathcal{U}_{USFUM_R}(\mathcal{G}(F_{LR});W_{SFUM_R};\odot), \quad (3)$$

where $\mathcal{U}_{SFUM_L}$ means the SFUM for left view image with learnable weights W_{SFUM_L}, and $\mathcal{U}_{SFUM_R}$ means the SFUM for right view image with learnable weights W_{SFUM_R} The left branch corresponds the feature unmixing to the global size image features for the left view image, and the right branch corresponds the feature unmixing to the global size image features for the right view image. The structure and processing of the SFUM will explained with the left branch below.

The left branch may have one or more fully connected (FC) layers, such as **412***a* and **414***a*, to reweight the corresponding channel information of the global size image features of the left view image, one or more ReLU layers and one or more sigmoid functions. In an example embodiment, a ReLU layer **413***a* is placed behind the first FC layer **412***a* and prior to the second FC layer **414***a*, and the activation function of sigmoid function **415***a* is placed behind the second FC layer **414***a* to range the values to (0,1).

$\odot$ represents the element-wise multiplication operation **416***a*. The different channels of the global size image features derived from the fused features F_{LR} are element-wise multiplied by the fused features, respectively, to reweight different channels of the fused features F_{LR} so as to generate $\tilde{F}_L$ as the left initial view-aware features and $\tilde{F}_R$ as the right initial view-aware features. For example, regarding the output of the convolutional block **212** corresponding to the fused feature with ½ of the spatial sizes of the output images of input convolutional block **211**, $\odot$ of SFUM **2201***a* element-wise multiplies the Red, Green, and Blue color channels of the left view image in the global size image features by the Red, Green, and Blue color channels of the left view image in the fused features F_{LR} respectively, to generate the Red, Green, and Blue color channels of the left view image of the left initial view-aware features. SFUM **2201***b* performs the similar generation for the right initial view-aware feature regarding the same spatial size as SFUM **2201***a*. The other SFUMs **2202***a*/**2202***b*, **2203***a*/**2203***b* correspond to respective generations of left and right view-aware features regarding different spatial sizes. That is, SFUM uses a learning-based method to reweight the channel information based on the input fused features from the backbone network **210**.

The FC layers, ReLU layer, activation function, and the element-wise multiplication operation in the right branch of SFUM for the right view image are similar and will not be described in details again.

Considering, that only reweighting the channel information cannot completely solve the spatial position mixing problem, a guided-feature unmixing module (GFUM) is introduced for generating the view-aware features so as to further unmix the spatial information, after getting the initial view-aware features $\tilde{F}_L$ and $\tilde{F}_R$. FIG. **4**B illustrates the structure of the guided-feature unmixing module (GFUM) of the feature unmixing sub-network **220** of the SNFU according to an exemplary embodiment of present disclosure.

Because the left view and right view images have different information for 3D object position, they are used to guide the feature unmixing as:

$$F_L=\mathcal{U}_{GFUM_L}(I_L;\tilde{F}_L;W_{GFUM_L};\odot),F_R=\mathcal{U}_{GFUM_R}(I_R;\tilde{F}_R;W_{GFUM_R};\odot), \quad (4)$$

where $\mathcal{U}_{GFUM_L}$ and W_{GFUM_R} represent the GFUM for left view and right view with corresponding learnable weights, respectively.

The GFUM is designed for each of the left and right view images. As shown in FIG. **4**B, the left part corresponds to the GFUM structure for left view image, wherein each of the reference numbers has a last character of "a", and the right part corresponds to the GFUM structure for the right one with last character of "b". For example, for the left view image part, the GFUM uses a downsampling layer **421***a* to downsample the left view image, i.e., the single view image of the paired images, to match the spatial size with the initial view-aware feature $\tilde{F}_L$. For example, GFUM **2211***a* needs to downsampling the left view image I_L to the spatial size of ½ of the spatial sizes of the left view image which is the same as the spatial size of the image feature outputted by the convolutional block **212**, since the initial view-aware feature output by the SFUM **2201***a* also has ½ of the spatial sizes of the left view image. GFUMs **2212***a* and **2213***a* downsample the left view image by same degree of the spatial size as SFUM **2202***a* and **2203***a* respectively.

Still illustrated with the left part of FIG. **4**B, GFUM uses one or more convolution layers with different kernels, for example, a convolutional layer **422***a* with 3×3 kernels, to generate a left spatial gate. The left spatial gate generated by the left view image has the spatial position information for 3D objects in left view image. The spatial position information is inputted into the activation function Sigmoid **423***a* and then element-wise multiplied by the left initial view-aware feature $\tilde{F}_L$ to generate left view-aware feature F_L. That is, the element-wise multiplication operation **424***a* between the left spatial gate and the left view image extracts the spatial position information relative to the left view image in the fused features to finish the feature unmixing. The element-wise multiplication operation **424***a* is similar to the operation **416***a* in SFUM and will not be detailed again. GFUMs **2212***a* and **2213***a* perform similar feature unmixing functions as GFUM **2211***a*.

For the right part of FIG. **4**B, GFUM **2211***b* downsamples the right view image with downsampling layer **421***b*, uses one or more convolution layers with different kernels, for example, convolutional layer **422***b* with 3×3 kernels, to generate a right spatial gate, and element-wise multiplies the output of the activation function Sigmoid **423***b* by the right initial view-aware feature $\tilde{F}_R$ to generate right view-aware feature F_R, so as to extract the spatial position information relative to the right view image in the fused features to finish the feature unmixing. GFUMs **2212***b* and **2213***b* perform similar feature unmixing functions as GFUM **2211***b*.

In fact, different sides of view images have invalid spatial correlations. Based on the spatial correlation characteristics between the view images of the left and the right and the initial view-aware feature of the view image of left and right, the result of the element-wise multiplication operation for different view images will be excluded and only the result for same side is kept. Therefore, the multiplication operations in SFUM and GFUM are only applied to the channels of the corresponding features of same view image.

From another view, the feature unmixing sub-network comprising SFUMs and GFUMs can be considered as many sub-units corresponding to different spatial sizes relative to the output of the convolutional blocks in the backbone network **210** for both the left and the right view images, each of which has a SFUM structure and a GFUM structure.

After the left and right view-aware features F_L and F_R for all of the downsampling convolutional blocks **212**, **213**, and **214** are generated, they are used for 3D object prediction, in step S**340**, where the prediction comprises left prediction **230***a* and right prediction **230***b*. The 3D object prediction is performed by prediction heads. As the details of the prediction heads are not the emphasis of present disclosure, they can be selected based on the previous solutions known.

In step S**350**, the method for 3D object detection according to an exemplary embodiment of present disclosure determines the spatial features of the 3D object predicted in the 3D object prediction, such as, by solving the 3D box **240**, to output final results. The 3D box of object can be defined by the spatial features of width, height, and depth of the 3D object.

SNFU is a deep CNN method. Thus, before the 3D object detection solution including the share network of SNFU, prediction heads, and the unit for solving the 3D box is used, for example, the share network of SNFU is used for extracting the fused features generated from the paired images and/or for unmixing the fused features to left and right the view-aware features, the network of SNFU is trained based on training data set to optimize the parameters.

Firstly, the architecture of SNFU is designed. The design work comprises the architecture of the backbone network (i.e. a feature extractor network), SFUMs, GFUMs, prediction heads, and the spatial feature determination unit for solving the 3D box. Among that, the typical architectures, such as ResNet, VGG, DenseNet, and search-based networks can be adopted as the backbone network. SFUMs and GFUMs can be designed according to the introduction with reference to FIGS. **4**A and **4**B. The prediction head can be adopted as specified in previous 3D object detection methods.

After designing the basic architecture of SNFU, we can prepare a set of training data including view images and their ground truth for supervised training. Because the networks are trained deeply using a lot of training samples, data augmentation operation like image flipping, and adding Gaussian noise can be adopted for better effect.

Regarding the parameter initialization, the network can be trained from scratch or by using pre-training weights for fine-tuning. If training the network from scratch, the parameters in the SNFU can be initialized randomly by Gaussian, Xavier or other methods in deep CNN. If a pre-trained network is provided, the weights in the convolutional layers of the input convolutional block **211** can be copied and pasted to meet the input demands.

Based on above preparation work, the share network of SNFU is trained by forward propagation and backward propagation iteratively. During the training, loss functions can be designed as previous 3D object detection methods. The parameter optimization can also adopt algorithms like SGD or Adam iteratively until convergence.

FIG. **5** shows the application for autonomous driving by the 3D object detection via the share network of SNFU according to an exemplary embodiment of present disclosure. Vehicle **510** has a stereo camera system **520** comprising a left camera **520***a* and a right camera **520***b*. Each of the cameras captures view images to generate paired images **530** which contain the 3D information of the objects. After being inputted into the onboard computation device embedding SNFU **540** of present disclosure, the 3D object detection and stereo localization operation transform the paired images **530** to a stereo image with 3D boxes indicating the detected 3D objects as shown by the rectangle boxes **550-1**. Then the autonomous driving unit or the driver of vehicle **510** can use the detection result to make decision for driving assistance.

The following shows experiments for binocular-based 3D object detection with SNFU according to exemplary embodiments of present disclosure vs. previous detection solutions.

KITTI dataset is chosen for evaluating the performance of the proposed 3D object detection with SNFU. KITTI dataset, in which 3D information of objects is provided for evaluation, is collected in practical driving scenes for autonomous driving research. The experimental share network of SNFU uses a ResNet-101 network to make a fair comparison with previous state-of-the-art solution with Stereo-RCNN network. The detection precision (using AP3d under 0.7 IoU metric in easy, moderate, and hard subsets, higher is better), and computation complexity (using GFlops, lower is better) are presented in Table 1. As can be seen, the 3D object detection solution of present disclosure can reduce the computation complexity by about 50% of that in baseline solution with Stereo-RCNN network while achieving the similar even better detection precision.

TABLE 1

Detection performance and computation comparison

	AP 3d			
Solution	easy	moderate	hard	Gflops
Stereo-RCNN	54.11	36.69	31.07	502.45
SNFU	55.02	38.23	32.35	261.79

In the step of S**350**, the detected 3D object can be represented by the solved spatial features of width channel, height channel, and depth channel. These spatial features define the location information of the 3D objects, for example, by a rectangle with the solved width, height, and depth. According to an exemplary embodiment of present disclosure, the 3D box solving manner can be further improved.

Depth estimation is a classical computer vision problem which describes the distance between observation point and 3D objects. In the situation of autonomous driving, getting the information of depth can avoid the accident of autonomous vehicle crashing into car and pedestrian. Meanwhile, the depth information is also helpful in 3D object detection and segmentation tasks. Therefore, the accuracy and the speed are two important points which the researchers concern the most.

FIG. **6** is the fundamental of stereo depth estimation for 3D object by using stereo camera. The pair of cameras, Camera L as the left camera and Camera R as the left camera, of the stereo camera device capture the stereo view images of 3D object which is the target of depth estimation. The points on the vertical axis are the observed images in left and right view of the 3D object obtained by left and right camera. According to the principle of similar triangle, the depth "z" of the 3D object away from the stereo camera can be easily determined by the relevant distance between the two cameras "b", the focus of the cameras "f", and the disparity between the images in the left and right view, $x_l - x_r$. Since b and f are easy to get, the depth estimation problem for 3D object detection turns to be a disparity estimation problem.

There are several existing depth estimation methods based on deep learning which are DispNet, GCNet, PSMNet, and GANet, for example. DispNet is the first end-to-end network for depth estimation. The method uses deep convolutional layers to extract the feature maps of left and right view images and then concatenate them together, and finally refines the concatenated features to get the predict disparity. However, the accuracy of DispNet is not good enough. GCNet involves feature extraction, cost volume and cost aggregation into an end-to-end CNN network which achieves high accuracy. Cost volume is a 4D tensor with the size of (max_disparity, channel, height, width). To deal with cost volume, the cost aggregation with many 3D convolution operation has to be involved which cost a lot of computation. PSMNet uses pyramid feature extraction and stacked hourglass block with 25 3D convolutional layers to improve the performance of the network. Similar to GCNet, the problem in PSMNet is the too much computation cost by 3D convolution operation. GANet uses a Semi-Global Guided Aggregation(SGA) model and a Local Guided Aggregation(LGA) model which achieve the state-of-the-art performance in depth estimation task, where the method uses different amount of SGA to balance the accuracy and efficiency.

In order to improve the speed of depth estimation without decrease the accuracy, the exemplary embodiment of present disclosure proposes a Paired Channel (abbreviated as "PC") Cost Volume Network (called as PCNet) which uses a cross concatenate operation with a 3D convolution layers to learn the correlation between left and right view images. The depth estimation for 3D object involves a 2D convolutional refinement instead of the 3D cost aggregation used, for example, in GCNet, PSMNet, and GANet.

FIG. **7** illustrates a diagram of a framework of the paired channel cost volume network (PCNet), as a 3D object localization approach, according to an exemplary embodiment of present disclosure. The proposed PCNet contains three main parts which are feature extraction sub-network **720**, paired channel (PC) module **730**, and refinement module **750**.

The feature extraction sub-network **720** extracts feature maps of the pair of the view images, i.e., the left view image **710***a* and right view images **710***b* which corresponding to the left and right view images of the pair of the view images **201** as shown in FIG. **2**. Compared to the inputted view images of FIG. **2**, the 3D objects are identified or predicted in the left and right view images **710***a* and **710***b*, for example, by the 3D object prediction operation **230***a* and **230***b* as mentioned above. The inputs of the feature extraction sub-network **720** are shown by the solid lines **1041***a* in FIG. **10**. The left and right view images **710***a* and **710***b* have the spatial information of the predicted 3D object. The feature extraction sub-network **720** can use two stacked hourglass structure with dense connection which are capable of extracting the feature maps of the left and right images effectively. The convolutional neutral network structure of two stacked hourglass structure with dense connection is known in previous method, for example, the two stacked hourglass structure can be based on a PSMNet and/or a simplified PSMNet or the other networks for depth estimation. The output of the feature extraction sub-network **720**, i.e., the feature map **731***a* of the left view image and the feature map **731***b* of the feature map of the right view image, are fed to PC module **730**. The feature maps **731***a*, **731***b* of the left and right view images may comprise the width and height of the 3D object, and the RGB color channel information of the left and right view images **710***a* and **710***b* additionally, that is, the feature maps **731***a* and **731***b* comprises two channels of spatial information of width and height of 3D object, and three channels of color information representing the 3D spatial information additionally.

The lower part of FIG. **7** shows the details of the Paired Channel module (PC module) **730**. The PC module **730** is the core of the PCNet method which has a Spatial Pyramid Pooling (SPP) structure with three parallel Paired Channel (PC) feature volumes **732**. PC feature volume **732** is constructed by one channel from the feature map **731***a* of the left view image and the corresponding channel from the feature map **731***b* of the right view image along the respective channel dimensions of the feature maps of the left and right view images. The way of forming PC feature volume **732** is named as "Cross Concat". For example, firstly for width channel, the width information in the width channel of the feature map **731***a* of the left view image **710***a* and the width information in the width channel of the feature map **731***b* of the right view image **710***b* are concatenated into the concatenated width channel; then for the height channel, the height information in the height channel of the feature map **731***a* of the left view image **710***a* and the height information in the height channel of the feature map **731***b* of the right view image **710***b* are concatenated into the concatenated height channel; and then for the RGB color channels, the RGB information in the RGB channels of the feature map **731***a* of the left view image **710***a* and the RGB information in the RGB channels of the feature map **731***b* of the right view image **710***b* are concatenated into the concatenated RGB channels respectively in sequence of R-G-B; finally for the whole channels, the concatenated width, height, and RGB channels are concatenated into the PC feature volume **732** respectively in sequence of width-height-RGB. Such cross concat operation can keep the information belonging to different channels not being interfered when performing the convolution and get the correlation between the channels of the feature maps of left and right view images instead of the feature inside the channels.

Then the PC feature volumes **732** are outputted to three small 3D convolutional filters **733***a*, **733***b*, and **733***c*, which is called as Paired Channel Filter (PC Filter), with the size of (k, k, 2) and the stride of (1, 1, 2), where k in the size (k, k, 2) represents different spatial sizes to extract the infor-

mation about depth, and 2 in the size (k, k, 2) represents the spatial relationship between two corresponding channels, i.e., the one channel of the feature map **731***a* of the left view image **710***a* and the corresponding channel of the feature map **731***b* of the right view image **710***b* with respect to same channel, such as height channel, for same 3D object. In FIG. **7**, it shows three PC filter of sizes (3×3×2), (5×5×2), and (7×7×2), which means the PC module **730** processes the spatial relationship between the channel information of the pair of view images with three spatial sizes. The stride can be selected based on actual demands. The PC filters **733***a* to **733***c* are constructed by small 3D convolutional layers to reduce the computation complexity. Then the outputs of three 3D convolutional layers are concatenated together to form the Spatial Pyramid Pooling structure, and a nonlinear function **734**, such as activation function Sigmoid, activates the results of convolution. The design of the PC filters makes sure that the filters only generate the correlation between the feature maps of the left and right view images without involving the inner feature information. The PC module **730** outputs a coarse disparity **740** of the 3D object as display in the view images.

In refinement module **750**, at least one stacked residual block, such as six stack residual blocks, R1, R2, . . . , R6 in FIG. **7**, are used for refining the coarse disparity **740** to a fine disparity **760** as display in the view images. According to an exemplary embodiment, the refinement module **750** is constructed by 2D convolutional layers which save a lot of computation compared with the cost aggregation with 3D convolutional layers used in GCNet, PSMNet and GANet. As for supervision, the output of PC module **730** and the output of refinement module **750** can be combined together to generate the final prediction of fine disparity.

The PCNet may further comprise a transform module to transform the fine disparity to the depth of the 3D object according to the similar triangle theory abovementioned.

Alternatively, in an exemplary embodiment of the present disclosure, the PCNet can also use the fused features extracted by the single backbone network **210** of the SNFU network in FIG. **2**, or use the left and right view-aware features unmixed by the feature unmixing sub-network of the SNFU network in FIG. **2** as the left and right feature maps outputted to the PC module **730**. Therefore, the function of the feature extraction sub-network **720** can be performed by the shared network of SNFU, especially the single backbone network of the SNFU, i.e., the fused features outputted by the backbone network **210** of SNFU or the left and right view-aware features outputted by the GFUM of SNFU are directly applied to the PC module **730** as the left and right feature maps **730***a* and **730***b*, as shown by the dotted lines of **1042***b* in FIG. **10**. In addition, the 3D object prediction information on the image segmentation in prediction operation **230***a* and **230***b* is also used in the PC module **730**.

The PCNet, as a convolutional neutral network, is trained based on a training data set before it is used for determining the disparity of 3D object. Following is an exemplary training method for PCNet. In the data preparation step of the training process, the training images with disparity labels of 3D objects are provided. Since the disparity labels obtained by LiDAR are sparse, a mask method can be used as preprocessing.

In the architecture step for the PCNet, the feature extraction sub-network **720** of two stacked hourglass structure with dense connection is configured to extract the feature maps of the left and right view images. After that, PC module **730** is configured to learn the correlation between the feature maps **731***a* and **731***b* of the left and right view images to get the coarse disparity. Then the refinement module **750** is configured to deal with the output of PC module **730** in order to get fine disparity as the final prediction of disparity is configured. In specific, the PC filters of the PC module **730** are selected as three 3D convolutional layers with the sizes of 3×3×2, 5×5×2, 7×7×2 and a stride of (1, 1, 2), and concatenated together to be activated for generating the coarse disparity.

Based on the training data set, the parameters of the network PCNet established are optimized. The parameters of the convolutional layers of PC filters and the parameters of the activation function f are obtained by minimizing the mean squared error of the training data set. The standard back-propagation algorithm can be used for solving the minimization problem. In the back-propagation algorithm, the gradients of the mean squared error with respect to the parameters of the PC filters and parameters of the activation function f are computed and back-propagated. The back-propagation algorithm is conducted in several epochs until convergence. To fasten the training, PCNet network can be trained on Scene Flow dataset as a pretrain, then be fine-tuned on KITTI 2015 dataset for autonomous driving.

After many steps of training, the final weights can be used to test the performance of depth prediction from images in testing dataset. The test computes EPE Error and Error Rate to evaluate the performance of the network.

In the experiments, Scene Flow dataset is chosen as the pretrain dataset for its large amount of stereo image. KITTI 2015 is chosen as the finetune dataset because it is the real-world street scene with fine labeled stereo images. An ablation study is performed and the experimental result of the PCNet is also compared with the state-of-the-art algorithm GANet. The comparison results are shown in Table 2 as follows:

TABLE 2

Results of experiment on KITTI 2015 Validation dataset

	Input		3D Conv			EPE	Error	
Method	Resolution	Pretrain	3 × 3 × 2	5 × 5 × 2	7 × 7 × 2	Error	Rate	Time(s)
DispNet	300 × 1000	Yes	—	—	—	1	4.65%	0.05
GANet-1	300 × 1000	Yes	—	—	—	0.7	3.21%	0.06
GANet-15	384 × 1248	Yes	—	—	—	—	2.71%	0.36
PCNet	384 × 1248	No	Yes	No	No	1.85	12.90%	0.11
PCNet	384 × 1248	Yes	Yes	No	No	0.83	2.90%	0.11
PCNet	384 × 1248	Yes	Yes	Yes	No	0.77	2.80%	0.11
PCNet	384 × 1248	Yes	Yes	Yes	Yes	0.75	2.68%	0.12

From the table 2, it can be seen that the proposed PCNet achieves competitive accuracy and higher speed compared with other methods. Row five shows the importance of pretrain. Rows six to eight show the effectiveness of SPP structure.

FIG. **8** illustrates graph on the result of comparison between PCNet and other method according to an exemplary embodiment of present disclosure. From the intuitive comparison between PCNet and other stereo depth estimation methods, it can be concluded that the proposed PCNet (marked by cross) gains better Error Rate compared with GANet-1, DispNet, and Toast. The proposed PCNet has similar Error rate but higher speed compared with GANet-15.

The following table 3 is the comparison of GFLOPS and parameter between PCNet and GANet. Index of GFLOPS is the computation cost of the network and index of parameter is the size of the network. According to the two indexes, the proposed PCNet has smaller size compared with GANet. That is why PCNet achieves higher speed.

TABLE 3

GFLOPS and parameter comparison between PCNet and GANet

Method	GFLOPS	parameter
GANet-15	1109	4.48M
PCNet	116	2.64M

FIG. **9** illustrates the predicted depth of PCNet on KITTI 2015 dataset. The upper row is original image. The middle row is the predicted depth (yellow, green red and blue mean the distance from small to large). The lower row is the difference between the predicted depth estimation and labels (the cooler color is better).

The present disclosure also provides a device for 3D object detection, as shown in FIG. **10**. The device **1000** comprises a fused image generation unit **1010**, a share network with feature unmixing (SNFU) **1020**, a prediction unit **1030**, and optional an object determination unit **1040**.

The fused image generation unit **1010** is configured to generate one or more fused images based on a pair of images, the pair of images including a left view image and a right view image, obtained from a stereo camera **1001**, e.g. two still image cameras or two video cameras. The fused images are generated by concatenating the channels of the left and right view images along respective channel dimensions.

The SNFU **1020**, as the main network structure of the device, comprises a single backbone network **1021** configured to extract one or more fused features from the pair of images and a feature unmixing sub-network **1022** configured to unmix the fused features to a left view-aware feature and a right view-aware feature. The feature unmixing sub-network **1022** further comprises SFUM **1023** and GFUM **1024**. The detail structures of the backbone network **1021** and the SFUM **1023** and GFUM **1024** are described above with reference to the framework in FIG. **2**, where the SFUM **1023** has a first multiplication sub-unit to perform the element-wise multiplication operation **416***a* and/or **416***b* in FIG. **4**A, and the GFUM **1024** has a second multiplication sub-unit to perform the element-wise multiplication operation **424***a* and/or **424***b* in FIG. **4**B.

The prediction unit **1030** is configured to predict the 3D object based on the left view-aware feature and the right view-aware feature.

The optional object determination unit **1040** is further configured to determine spatial features of the predicted 3D object. In an embodiment, the object determination unit **1040** is further configured as a PCNet structure comprising a Feature extraction sub-network **1041**, a PC module **1042**, a refinement module **1043**, and a transformation module **1044**.

Comparing with previous binocular based 3D object detection solutions, the proposed 3D object detection with share network of SNFU according to embodiment of present disclosure has the following advantages:

In the 3D object detection with SNFU, only a share backbone network is used for feature extraction of paired images, which is much more efficient than adopting two networks for feature extraction. Such architecture of single backbone network can dramatically reduce the computation complexity and improve the detection efficiency, which promotes the practical application of stereo vision. Features for left view and right view images are interacted in the backbone network and separated by using SFUM and GFUM. This mechanism guarantees the view-aware prediction and accurate detection performance.

In addition, the 3D object detection with SNFU can be developed into multi-view system in which several paired images are processed simultaneously. The share network of SNFU can effectively control the computation complexity, while previous method, especially the two-stream network scheme, will double and redouble the computation complexity linearly.

Furthermore, the PCNet proposed by the exemplary embodiment of present disclosure can achieve the competitive performance on accuracy and high speed simultaneously when predicting the depth of the 3D object, so as to achieve better performance in the autonomous driving system.

FIG. **11** illustrates a computer system, apparatus or device **1100** upon which an exemplary embodiment of the disclosure can be implemented. Although computer system **1100** is depicted with respect to a particular device or equipment, it is contemplated that other devices or equipment (e.g., network elements, servers, etc.) within FIG. **11** can deploy the illustrated hardware and components of system **1100**. Computer system **1100** is designed and is programmed (e.g., via computer program code or instructions) for decentralized trust evaluation in a distributed network as described herein and includes a communication mechanism such as a bus **1110** for passing information between other internal and external components of the computer system **1100**. Information (also called data) is represented as a physical expression of a measurable phenomenon, typically electric voltages, but including, in other embodiments, such phenomena as magnetic, electromagnetic, pressure, chemical, biological, molecular, atomic, sub-atomic and quantum interactions. Computer system **1100**, or a portion thereof, constitutes a means for performing one or more steps of security and trust technologies and solutions in virtualized networks. The computer system, apparatus or device **1100** can be, can be implemented in, can be embedded in, can be communicatively attached to, can be communicatively connected to, for example, a vehicle, a vehicle electronic control unit (ECU), a mobile phone, a mobile communication device, a game device, a smart glasses, a camera element, a video camera, a still image camera, a personal computer, a service device, or any combination thereof.

A bus **1110** includes one or more parallel conductors of information so that information is transferred quickly among

devices coupled to the bus **1110**. One or more processors and/or circuitries **1102** for processing information are coupled with the bus **1110**.

The stereo camera to capture the pair of the view images can be directly connected to the bus **1110** so as to transfer the view images to other devices coupled to the bus **1110**. Alternatively, the stereo camera can also communicate with the computer system, apparatus or device **1100** via the communication interface **1170** as described below.

A processor **1102** performs a set of operations on information as specified by computer program code related to the decentralized trust evaluation in a distributed network as described herein. The computer program code is a set of instructions or statements providing instructions for the operation of the processor and/or the computer system to perform specified functions. The code, for example, can be written in a computer programming language that is compiled into a native instruction set of the processor. The code can also be written directly using the native instruction set (e.g., a machine language). The set of operations include bringing information in from the bus **1110** and placing information on the bus **1110**. The set of operations also typically include comparing two or more units of information, shifting positions of units of information, and combining two or more units of information, such as by addition or multiplication or logical operations like OR, exclusive OR (XOR), and AND. Each operation of the set of operations that can be performed by the processor is represented to the processor by information called instructions, such as an operation code of one or more digits. A sequence of operations to be executed by the processor **1102**, such as a sequence of operation codes, constitute processor instructions, also called computer system instructions or, simply, computer instructions. Processors can be implemented as mechanical, electrical, magnetic, optical, chemical or quantum components, among others, alone or in combination.

As used in this application, the term circuitry may refer to one or more or all of the following:

(a) hardware-only circuit implementations (such as implementations in only analog and/or digital circuitry) and

(b) combinations of hardware circuits and software, such as (as applicable):

(i) a combination of analog and/or digital hardware circuit(s) with software/firmware and

(ii) any portions of hardware processor(s) with software (including digital signal processor(s)), software, and memory(ies) that work together to cause an apparatus, such as a mobile phone or server, to perform various functions) and

(c) hardware circuit(s) and or processor(s), such as a microprocessor(s) or a portion of a microprocessor(s), that requires software (e.g., firmware) for operation, but the software may not be present when it is not needed for operation."

This definition of circuitry applies to all uses of this term in this application, including in any claims. As a further example, as used in this application, the term circuitry also covers an implementation of merely a hardware circuit or processor (or multiple processors) or portion of a hardware circuit or processor and its (or their) accompanying software and/or firmware. The term circuitry also covers, for example and if applicable to the particular claim element, a baseband integrated circuit or processor integrated circuit for a mobile device or a similar integrated circuit in server, a cellular network device, or other computing or network device.

Computer system **1100** also includes a memory **1104** coupled to bus **1110**. The memory **1104**, such as a random access memory (RAM) or other dynamic storage device, stores information including processor instructions for decentralized trust evaluation in a distributed network as described herein. Dynamic memory allows information stored therein to be changed by the computer system **1100**. RAM allows a unit of information stored at a location called a memory address to be stored and retrieved independently of information at neighboring addresses. The memory **1104** is also used by the processor **1102** to store temporary values during execution of processor instructions. The computer system **1100** also includes a read only memory (ROM) **1106** or other static storage device coupled to the bus **1110** for storing static information, including instructions, that is not changed by the computer system **1100**. Some memory is composed of volatile storage that loses the information stored thereon when power is lost. Also coupled to bus **1110** is a non-volatile (persistent) storage device **1108**, such as a magnetic disk, optical disk or flash card, for storing information, including instructions, that persists even when the computer system **1100** is turned off or otherwise loses power.

Information, including instructions for decentralized trust evaluation in a distributed network as described herein, is provided to the bus **1110** for use by the processor from an external input device **1112**, such as a keyboard containing alphanumeric keys operated by a human user, or a sensor. Other external devices coupled to bus **1110**, used primarily for interacting with humans, include a display device **1114**, such as a cathode ray tube (CRT) or a liquid crystal display (LCD), or plasma screen or printer for presenting text or images, and a pointing device **1116**, such as a mouse or a trackball or cursor direction keys, or motion sensor, for controlling a position of a small cursor image presented on the display **1114** and issuing commands associated with graphical elements presented on the display **1114**. In some embodiments, for example, in embodiments in which the computer system **1100** performs all functions automatically without human input, one or more of external input device **1112**, display device **1114** and pointing device **1116** is omitted.

In the illustrated embodiment, special purpose hardware, such as an application specific integrated circuit (ASIC) **1120**, is coupled to bus **1110**. The special purpose hardware is configured to perform operations not performed by processor **1102** quickly enough for special purposes. Examples of application specific ICs include graphics accelerator cards for generating images for display **1114**, cryptographic boards for encrypting and decrypting messages sent over a network, speech recognition, and interfaces to special external devices, such as robotic arms and medical scanning equipment that repeatedly perform some complex sequence of operations that are more efficiently implemented in hardware.

The units in device **1000** of FIG. **10** can be stored in the read only memory **1106**, or the storage device **1108** as function modules comprising sets of instructions in form of computer program codes, such as software, firmware, and/or combination thereof. These function modules are read into memory **1104** and executed by the processor **1102** to perform the corresponding functionalities as mentioned above. The executions of these function modules can also be performed in the ASIC **1120** for its greater operational performance for special purpose. During the training process

for the network, the user can also input the training data set and modify the training parameters via the input device **1112**.

Computer system **1100** also includes one or more instances of a communications interface **1170** coupled to bus **1110**. Communication interface **1170** provides a one-way or two-way communication coupling to a variety of external devices that operate with their own processors, such as printers, scanners and external disks. In general, the coupling is with a network link that is connected to a local network to which a variety of external devices with their own processors are connected. For example, communication interface **1170** can be a parallel port or a serial port or a universal serial bus (USB) port on a personal computer. In some embodiments, communications interface **1170** is an integrated service digital network (ISDN) card or a digital subscriber line (DSL) card or a telephone modem that provides an information communication connection to a corresponding type of telephone line. In some embodiments, a communication interface **1170** is a cable modem that converts signals on bus **1110** into signals for a communication connection over a coaxial cable or into optical signals for a communication connection over a fiber optic cable. As another example, communications interface **1170** can be a local area network (LAN) card to provide a data communication connection to a compatible LAN, such as Ethernet. Wireless links can also be implemented. For wireless links, the communications interface **1170** sends or receives or both sends and receives electrical, acoustic or electromagnetic signals, including infrared and optical signals, that carry information streams, such as digital data. For example, in wireless handheld devices, such as mobile telephones like cell phones, the communication interface **1170** includes a radio band electromagnetic transmitter and receiver called a radio transceiver. In certain embodiments, the communication interface **1170** enables connection to virtualized networks for decentralized trust evaluation in a distributed network as described herein.

The term "computer-readable medium" as used herein refers to any medium that participates in providing information to processor **1102**, including instructions for execution. Such a medium can take many forms, including, but not limited to computer-readable storage medium (e.g., non-volatile media, volatile media), and transmission media. Non-transitory media, such as non-volatile media, include, for example, optical or magnetic disks, such as storage device **1108**. Volatile media include, for example, dynamic memory **704**. Transmission media include, for example, coaxial cables, copper wire, fiber optic cables, and carrier waves that travel through space without wires or cables, such as acoustic waves and electromagnetic waves, including radio, optical and infrared waves. Signals include man-made transient variations in amplitude, frequency, phase, polarization or other physical properties transmitted through the transmission media. Common forms of computer-readable media include, for example, a floppy disk, a flexible disk, hard disk, magnetic tape, any other magnetic medium, a CD-ROM, CDRW, DVD, any other optical medium, punch cards, paper tape, optical mark sheets, any other physical medium with patterns of holes or other optically recognizable indicia, a RAM, a PROM, an EPROM, a FLASH-EPROM, any other memory chip or cartridge, a carrier wave, or any other medium from which a computer can read. The term computer-readable storage medium is used herein to refer to any computer-readable medium except transmission media.

Logic encoded in one or more tangible media includes one or both of processor instructions on a computer-readable storage media and special purpose hardware, such as ASIC **1120**.

At least some embodiments of the disclosure are related to the use of the computer system or apparatus **1100** for implementing some or all of the techniques described herein. According to one embodiment of the disclosure, those techniques are performed by computer system **1100** in response to one or more processors **1102** executing one or more sequences of one or more processor instructions contained in one or more memories **1104**. Such instructions, also called computer instructions, software and program code, can be read into memory **1104** from another computer-readable medium such as storage device **1108** or network link. Execution of the sequences of instructions contained in memory **1104** are configured to cause processor **1102** to perform one or more of the method steps described herein. In alternative embodiments, hardware, such as ASIC **1120**, can be used in place of or in combination with software to implement the invention. Thus, embodiments of the invention are not limited to any specific combination of hardware and software, unless otherwise explicitly stated herein.

Some example embodiments of the disclosure relating to the computer system or apparatus **1100** can be implemented in a system, an apparatus or a device comprising at least one processor, and at least one memory including computer program code, the at least one memory and the computer program code configured to, with the at least one processor, cause the apparatus at least to perform the various functions as described relating to the FIGS. **1-5**, **7** and **10**.

The signals transmitted over network link and other networks through communications interface **1170**, carry information to and from computer system **1100**. Computer system **1100** can send and receive information, including program code, through the networks, through communications interface **1170**. The received code can be executed by processor **1102** as it is received, or can be stored in memory **1104** or in storage device **1108** or other non-volatile storage for later execution, or both. In this manner, computer system **1100** can obtain application program code in the form of signals on a carrier wave.

The present disclosure includes any novel feature or combination of features disclosed herein either explicitly or any generalization thereof. Various modifications and adaptations to the foregoing exemplary embodiments of this disclosure can become apparent to those skilled in the relevant arts in view of the foregoing description, when read in conjunction with the accompanying drawings. However, any and all modifications will still fall within the scope of the non-limiting and exemplary embodiments of this disclosure.

What is claimed is:

1. A method, comprising:

generating one or more fused images based on a pair of images, the pair of images including a left view image and a right view image;

extracting one or more fused features from the fused images by a single backbone network;

unmixing the fused features to a left view-aware feature and a right view-aware feature;

predicting a 3D object based on the left view-aware feature and the right view-aware feature; and

determining one or more spatial features of the predicted 3D object.

2. The method according to claim **1**, wherein the pair of the images is obtained by a stereo camera.

3. The method according to claim 1, wherein generating the one or more fused images based on the pair of the images further comprises:

generating the one or more fused images by concatenating the channels of the left and right view images along respective channel dimensions.

4. The method according to claim 1, wherein the backbone network comprises an input convolutional block and one or more downsampling convolutional block which are connected in sequence, the input convolutional block being configured to receive the fused images, the downsampling convolutional block, each of which comprises at least one convolutional layer, being configured to generate fused features comprising image features with different spatial sizes.

5. The method according to claim 1, wherein unmixing the fused features to the left view-aware feature and the right view-aware feature further comprises:

generating left initial view-aware features and right initial view-aware features based on the fused features; and

generating left view-aware features and right view-aware features based on the left initial left view-aware features and the right initial view-aware features.

6. The method according to claim 5, wherein generating the left initial view-aware features and the right initial view-aware features based on the fused features further comprises:

extracting global size image features from the fused features by a global average pooling operation and full convolution operations; and

generating the left initial view-aware features and the right initial view-aware features by reweighting different channels of the global size image features.

7. The method according to claim 5, wherein generating the left view-aware features and the right view-aware features based on the left initial left view-aware features and the right initial view-aware features further comprises:

downsampling the left and right view images according to the spatial sizes of the image features of the fused features, respectively;

generating spatial position information for the 3D object in the left and right view images respectively; and

generating the left and right view-aware features, based on the spatial position information for the 3D object in the left view image and the right view image, and the left initial view-aware features and the right initial view-aware features, respectively.

8. The method according to claim 7, wherein,

the left view-aware features are generated by element-wise multiplying the spatial position information for the 3D object in the left view image by the left view image, and

the right view-aware features are generated by element-wise multiplying the spatial position information for the 3D object in the right view image by the right view image.

9. The method according to claim 1, wherein the one or more spatial features of the 3D object comprise a height, a width, and a depth of the 3D object, determining spatial features of the predicted 3D object further comprises:

determining the depth of the 3D object based on the height and the width of the 3D object predicted in the left and right view images.

10. The method according to claim 1, wherein the 3D object detection is implemented in a vehicle.

11. The method according to claim 1, wherein the 3D object detection is implemented in a mobile communication device.

12. An apparatus comprising:

at least one processor; and

at least one memory storing instructions that, when executed by the at least one processor, cause the apparatus at least to:

generate one or more fused images based on a pair of images, the pair of images including a left view image and a right view image;

extract one or more fused features from the pair of images and a feature unmixing sub-network configured to unmix the fused features to a left view-aware feature and a right view-aware feature;

predict a 3D object based on the left view-aware feature and the right view-aware feature; and

determine one or more spatial features of the predicted 3D object.

13. The device according to claim 12, wherein the paired of images is obtained by a binocular imaging unit.

14. The device according to claim 12, further caused to generate the fused images by concatenating the channels of the left and right view images along respective channel dimensions.

15. The device according to claim 12, wherein the backbone network comprises an input convolutional block and one or more downsampling convolutional block which are connected in sequence, the input convolutional block being configured to receive the fused images, the one or more downsampling convolutional block, each of which comprises at least one convolutional layer, being configured to generate fused features comprising image features with different spatial sizes.

16. The device according to claim 12, further caused to:

generate left initial view-aware features and right initial view-aware features based on the fused features; and

generate left view-aware features and right view-aware features based on the left initial left view-aware features and the right initial view-aware features.

17. The device according to claim 16, further caused to element-wise multiply the global size image features by the fused features, respectively, to reweight the different channels of the global size image features.

18. The device according to claim 12, further caused to:

downsample the left and right view images according to the spatial sizes of the image features of the fused features, respectively;

generate spatial position information for the 3D object in the left and right view images respectively; and

generate the left and right view-aware features based on the spatial position information for the 3D object in the left and right view image and the left initial view-aware features and the right initial view-aware features, respectively.

19. The device according to claim 18, further caused to:

element-wise multiply the spatial position information for the 3D object in the left view image by the left view image to generate the left view-aware features; and

element-wise multiply the spatial position information for the 3D object in the right view image by the right view image to generate the right view-aware features.

20. The device according to claim 12, wherein the one or more spatial features of the 3D object comprise a height, a width, and a depth of the 3D object, further configured to

determine the depth of the 3D object based on the height and the width of the 3D object predicted in the left and right view images.

21. The device according to claim **12**, further caused to:

extract feature maps of the left and right view images from the left and right view images;

generate a coarse disparity based on the channels of the feature maps of the left and right view images;

refine the coarse disparity to a fine disparity; and

transform the fine disparity to the depth of the 3D object.

22. A non-transitory computer-readable medium comprising instructions which, when executed by an apparatus, cause the apparatus to perform at least the following

generating one or more fused images based on a pair of images, the pair of images including a left view image and a right view image;

extracting one or more fused features from the fused images by a single backbone network;

unmixing the fused features to a left view-aware feature and a right view-aware feature;

predicting the 3D object based on the left view-aware feature and the right view-aware feature; and

determining one or more spatial features of the predicted 3D object.

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