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Research Article

Efficient object detection method to Correcting images and videos from medium-resolution cameras using BEMD-based Scale-Invariant-Features-Transform: road safety application

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Abstract:

The Scale-Invariant-Features-Transform (SIFT) is a computer vision algorithm to detect and match local features in images. This algorithm is an indirect detection method since it doesn't consider the entire candidate object to be detected but works only on the most interesting points of the object which allows efficiency in blurred images and Real Time applications such as object recognition, video tracking and many other applications.The mean idea in the SIFT algorithm is to apply a derivative function in multiple scales. Then search the details (invariant key-points) across the derived scales.To create the scales, firstly, octaves are made using different sub-samplings on the template image containing the object to be detected or matched. Then multiple pass-bands Gaussian filters are applied on each octave to have its Gaussian-filtered scales.Then, the Laplacian filter is applied on each Gaussian-filtered scale to define scale-details called LOG (Laplacian of Gauss) on which the key-points will be searched. The invariant details called key-points will be the extrema points that persist as local extrema across the LOGs of the same octave scales.In this paper, we do the same to define the different scales and we propose to apply an improved version of the BEMD (Bi-dimensional Empirical Mode Decomposition) on the obtained different Gaussian-filtered scales to define the details which are the Intrinsic Mode Functions IMFs. In the proposed algorithm, since the IMFs are already obtained basing on the extrema points in a sifting process of the BEMD, no search will be done for the extrema points (key-points) across the BEMD-sifted components of Gaussian-filtered scales. In addition, since the BEMD gives locally ordered oscillating zero means components (the IMFs) from the most high spatial frequencies to the lowest ones then the continuous component (residue), the sifting process of the BEMD can be then stopped on only the first obtained IMF (containing the finest details) of each Gaussian-filtered scale which allows a computationally fast algorithm that can be used to quickly detect objects in a massive volume of data such as videos. Also, since an IMF is an oscillating mono-component free from any continuous component, the proposed BEMD-based SIFT algorithm allows correct detection of the object in different conditions such as blurred images, different sizes of the object and rotated objects. In this paper, in a first step, the proposed BEMD-based SIFT algorithm is applied to recognise the prohibitory traffic signs especially for speed limitation. In a second step, the speeding vehicles can be then automatically tracked by using the KLT algorithm (*Kanade-Lucas-Tomasi*) using motion vector thresholding in accordance with the already recognized sign of speed limitation by the proposed algorithm of detection.

1. Introduction

The object detection is needed in many artificial vision applications such as video tracking and object recognition. Direct object detection methods use the correlation coefficient to detect the entire object of the template image in the analysed image. This way of matching objects is on one side computationally slow and is not suitable for real time functioning. On the other hand, the direct methods for detecting objects are intensively sensible to the noise so they cannot be suitable for different environmental conditions.

The indirect methods consider only the key-points in the template (image containing the candidate object to detect) which allows them to be less sensible to the noise and computationally fast. The indirect methods are then more suitable for real time functioning and for different environmental conditions.

We can cite as indirect detector, the HARRIS detector and the SIFT Detector (Scale-Invariant-Features-Transform) [25], [26], [27]. The SIFT detector is mainly based on the details extraction in multiple scales of the template image. This algorithm uses a set of Gaussian-filters on different octaves (the octaves are obtained by the template image sub-samplings) to define the scales and then uses the Laplacian filter to extract their details. A search of the invariant details across each octave scale details is then done to define the interesting key-points for each octave.

In this paper, we propose a BEMD-based SIFT algorithm where an improved BEMD is used to extract the details in the different scales. The characteristics of the improved BEMD [28] components can allow the IMF's extrema to be the invariant details and avoid an extra time for the invariant details searching across each scale's details. The detection algorithm is applied to recognize speed limitation signs then a KLT algorithm is used to automatically (in accordance with the detection sign) follow the speeding vehicles.

These last years the EMD (Empirical Mode Decomposition) attracted many researchers for its interesting properties because it allows a description which is [1], [3], [5], [20]:

- Complete: the sum of all IMFs and the residue gives exactly the signal of origin,
- Orthogonal: avoid any redundancy in its representation in IMFs,
- Local: allows analyzing the non stationary signals,
- Adaptive: behaves qualitatively in a bench of adaptive auto- filters.

It was interesting to extend the EMD to two dimensions for the multi-components and/or non stationary images analysis [4], [6], [7], [9], [16], [19].

The BEMD (Bi-dimensional Empirical Mode Decomposition) is an extension of the EMD to be applied on image or 2-Dimentional signals. Several works were proposed to extend EMD to BEMB and apply it to many applications as filtering, image fusion, image coding .etc [8], [10], [11], [12], [15], [17], [18], [28].

These methods have shown satisfying results in different applications.In this work, we firstly propose a BEMD-based SIFT algorithm and apply it for speed limitation signs detection in an image or a video. Then the result of detection allows automatic follow up of the speeding vehicles using KLT algorithm. This paper is organized as follows: In Sec. 2, the SIFT algorithm is presented. The BEMD is presented and explained in Sec. 3. The proposed detection method is presented and developed giving experimental examples in Sec. 4. Then the proposed detection method allows automatic magnitude threshold definition for motion vectors of KLT algorithm applied to track speeding vehicles in a road safety application in Sec. 5. Discussions and conclusions are given at the end.

2. Scale-Invariant-Features-Transform

The Scale-Invariant-Features-Transform (SIFT) is a computer vision algorithm to detect, describe, and match local features in images, invented by David Lowe [25]. Its applications include object recognition, robotic mapping and navigation, 3D modeling, gesture recognition, video tracking, individual identification of wildlife and match moving [26].SIFT key-points of objects are first extracted from a set of reference images and stored in a database [25]. An object is recognized in a new image by individually comparing each feature from the new image to this database and finding candidate matching features based on Euclidean distance of their feature vectors. A SIFT algorithm synoptic scheme is given in Fig.1:

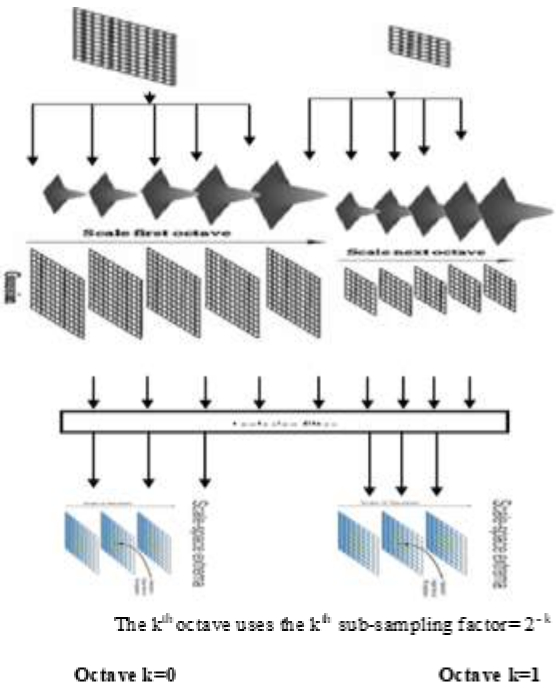

Figure 1. *Synoptic scheme for the SIFT algorithm applied on the template image.*

3. The Beam

Empirical Mode Decomposition EMD was firstly proposed to decompose 1-Dimensional non stationary signals into locally oscillating zero means components called IMFs (Intrinsic Mode Fuction). Locally, these IMFs are mono-component (so close to a sinusoid: since they are zero mean and between each two successive extrema there is a crossing by zero) and are, locally, in a descendent order of frequencies spectrums from the first IMF which is the richest IMF in high frequencies until the last one and then the residue component containing the continuous component in the signal.

The EMD is based on a sifting process. This sifting process is based on the signal minimums and maximums extraction and their interpolation obtaining upper and lower envelopes. The mean of these two envelopes is considered to be, locally, the lowest frequencies component in the signal. This mean envelope is subtracted from the signal in a repetitive process named sifting. This sifting is held until one IMF is obtained (when there is no mean envelope or a so small one to be subtracted from the resulting signal). Then the signal is updated by subtracting the last extracted IMF.This sifting process is repeated for each IMF extraction until obtaining signal having less than three extremas. It is the continuous component in the signal named residue of the EMD decomposition. The sum of all IMFs with the residue component reconstructs exactly the analysed signal. Then, the principle of the EMD [1], [2] is to decompose the signals into a sum of oscillatory functions (IMFs). An IMF has the following interesting characteristics:

a) is zero mean value,

b) has the numbers of extremas and zero crossing that differ at most by one (in other words, that means that between minimum and successive maximum, an IMF passes by zero),

c) follows a law of amplitude modulation and frequency (oscillating behavior) naturally of mono-component type.

A-Review of EMD

The EMD is an adaptive decomposition method that analyses locally a signal which allows to locally selecting the high frequencies to gradually move towards the lower frequencies.

IMFs extraction requires the following sifting steps [2]:

Step 1) Fixing ε (empirically between 0.2 and 0.3), j⟵1(jth IMF)

Step 2) $r_{j-1}(t)$ ⟵x(t) (residue)

Step 3) Extract the jth IMF :

(a) $h_{j,i-1}(t) \leftarrow r_{j-1}(t)$, i ⟵1 (i, iteration of the sifting loop*)*

(b) Extract the local maxima and minima of $h_{j,i1}(t)$

(c) Calculate the upper and lower envelopes: $U_{j,i-1}$ (t) et $L_{j,i-1}$ (t) by interpolation (Cubic Splines [14]) with the local maxima and minima of $h_{j,i-1}(t)$ respectively.

(d) Calculate the average envelope: $\mu_{j,i-1}(t) = (U_{j,i-1}(t) + L_{j,i-1}(t))/2$.

(e) Update: $h_{j,i}(t) \leftarrow h_{j,i-1}(t) - \mu_{j,i-1}(t)$, i⟵i+ 1.

(f) Calculate the stopping criterion [2]:

$$SD(i) = \sum_{t=0}^{T} \frac{\left| h_{j,i-1}(t) - h_{j,i}(t) \right|^2}{(h_{j,i-1}(t))^2} ,$$

Where T represents the number of the signal samples.

(g) Decide: repeat steps (b)-(f) until SD(i) ≤ε .

And then put $IMF_j(t) \leftarrow h_{j,i}(t)$ (jth IMF).

Step 4) Update the residue:

$r_j(t) \leftarrow r_{j.1}(t) - IMF_j(t)$, i⟵1.

Step 5) Repeat step 3 with j⟵j+1 until the number of extremas in $r_j(t)$ is less than 3.

B-EMD extension to BEMD

In the concern of the 2D extrema extraction, in the literature [32], [9], [33] the local extrema of an image are determined by its morphological structure by comparing each pixel with its 8 close pixels (related) [3], [4], [5], [21], [22], [23], [24]. For each area made up of a pixel and its 8 related pixels, the central pixel is candidate to be an extrema. Any candidate pixel having a value of intensity higher or lower to all the intensity values of its 8 related pixels, is taken respectively as a local maximum or a local minimum.

However, in [28], it was shown that this way to decide extrema elements is not faithful to the 1D signal extrema extraction using the EMD and can loss extrema points, for 1D signals around the considered pixel, without definition that gives 2D IMFs characteristics that are not granting as 1D IMFs (not purely oscillatory 2D IMFs around zero and not monotonous residue) refering to the analyzed images in [34], [33], [35], [3], [36], [4], [37], [5]) and among others. For that reason, the one main improvement proposed in [28] to the BEMD was to extract 2D extrema elements in an improved approach more faithful to the 1D extrema extraction as follows:

A pixel can be a maximum or a minimum element when its value is respectively greater or lower than the values of, at least, one 1D-signal across the considered pixel. The four 1D-signals, to be compared with the considered pixel, are composed of the closest neighborhood elements to the considered pixel and include it. They are the horizontal, vertical and the two diagonals lines across it [28].

For that reason, for our proposed detection method based on the BEMD, We adopt the extrema extraction approach proposed in improved BEMD [28].

Fig.2 shows the improved BEMD decomposition of a 256x256 spatial definition and 8 bits coded image that gives five IMFs and a residue.

Fig.2 shows also that the IMFs are, locally, in a descendent order of frequencies spectrums from the first IMF which is, locally, the richest IMF in high spatial frequencies (finest spatial details) until the last one and then the residue containing the continuous component.

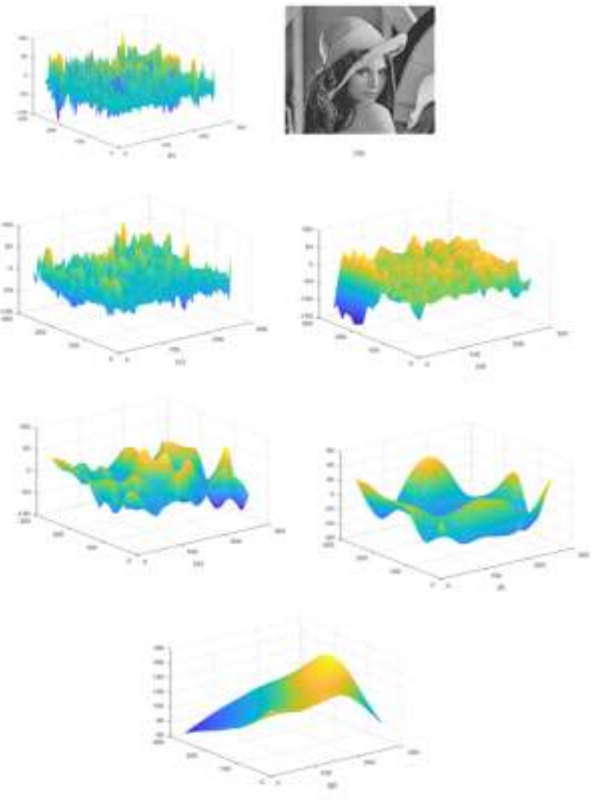

Figure 2.*BEMD image decomposition: (a) original image, (b) the 1^{st} IMF, (c) the 2^{nd} IMF, (d) the 3^{rd} IMF, (e) the 4^{th} IMF, (f) the 5^{th} IMF and (g) the residue component*

The mean values of the IMFs and residue obtained by applying the improved BEMD [28] on the image in (Fig-2-a) are -0.1030, 1.3638, 0.2099, 1.1133, -4.6833 and 126.0980 respectively for the first IMF, the second IMF, the third IMF, the fourth IMF, the fifth IMF and the residue (the continuous component). That shows IMFs with close zero mean values and a residue containing the continuous component in the image. These IMFs mean values so close to zero can allow to the meaning that these IMFs are mono-component (so close to a sinusoid: since they are zero mean and between each two successive extrema there is a crossing by zero). On the one hand, since the sifting process of the BEMD is based on the image minimums and maximums extraction that gives oscillating mono-components (locally close to a sinusoid), the IMFs can be considered as the invariant details avoiding an extra time for invariant details searching across each scale's details. Also, being pure details (oscillating mono-components with zero mean values), the IMFs don't contain the continuous component, that is sifted in the residue component, and can be then easily detected independently to the object gray scale or colour neither to the various illumination conditions.

On the other hand, the first IMF contains the finest details then the sifting process of the BEMD applied on the Gaussian-filtered scales of the template image (containing the candidate object) can be stopped at the first IMF to be later considered as the key-points of the details to be matched or detected on the first IMF of the image on which we aim to detect objects.

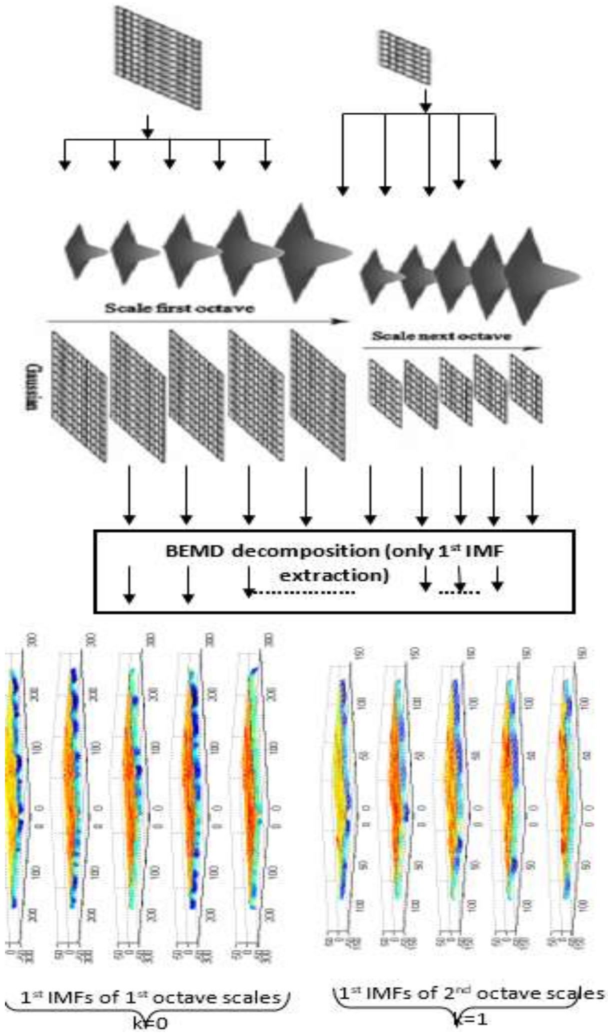

Figure 3. *Synoptic scheme for the BEMD-based SIFT algorithm.*

4. BEMD-Based Scale-Invarient-Features-Transform

In this section, we aim to develop and show experimental examples for the proposed BEMD-based SIFT algorithm. The main difference between the SIFT algorithm and the proposed BEMD-based SIFT algorithm is in the details extraction method and in the definition of the key-points to be matched or detected.

Unlike the SIFT algorithm that uses the Laplacian filter on the Gaussian-filtered scales to extract their details and then searches across the different Laplacian-filtered scales for the invariant details (key-points), the proposed BEMD-based SIFT algorithm uses improved BEMD [28] on the Gaussian-filtered scales to extract only the 1st IMFs components.

While the IMFs are locally pure mono-component details already defined on the extrema extraction in a sifting process and are free from any continuous component, this allows their extrema pixels to be the key-points to be matched independently to the object gray scale or color neither to the various illumination conditions.

The first IMF, being the finest local details, its extrema elements can be considered as the key-points to be matched and the improved BEMD [28] sifting process can be then stopped at the first component extraction.

The extrema matrixes of the first IMFs of each Gaussian-filtered scale of the template are to be matched in the extrema matrix of the first IMF of the image on which we aim detect objects. The detection spatial location on the analyzed image is the same as that on its 1st IMF's extrema matrix.

The BEMD-based SIFT algorithm is computationally fast since it uses only one IMF and doesn't search for invariant details (key-points) due to the IMF's pure oscillatory nature.

Fig.3 shows a synoptic scheme to the BEMD-based SIFT algorithm.

The k^{th} octave uses the k^{th} sub-sampling factor= 2^{-k}

The example given in Fig.4 shows the efficiency of the proposed BEMD-based SIFT algorithm. The analyzed image contains objects in different conditions: blurred objects (random noise), different object sizes and rotated objects. The areas, in Fig.4, in red rectangles are the detected objects. Fig.4 shows that the BEMD-based SIFT algorithm allows correct detection of the object in different conditions such as blurred objects, different sizes of the object and rotated objects. This is mainly due to the use of the IMFs components that are locally pure mono-component details free from any continuous component which allows an efficient

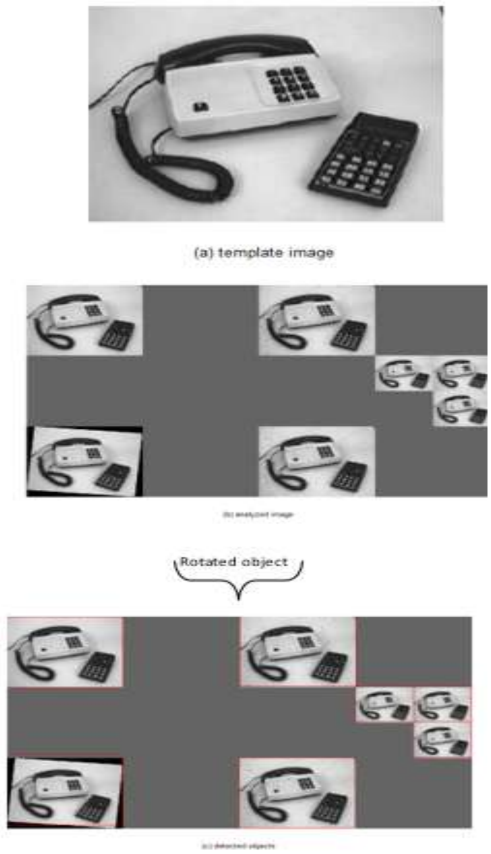

Figure 4. *BEMD-based SIFT algorithm example: (a) the template image containing the object to be detected (b) the analyzed image containing rotated object, different object sizes and random blurred objects, (c) the detected objects in red rectangles.*

detection in various conditions of illumination, noise...EtcIn the example of Fig.4, two octaves are considered. The following figure shows the used octaves and their obtained Gaussian-filtered scales.

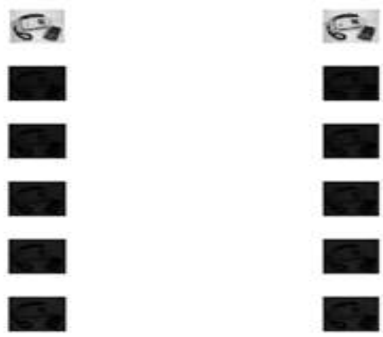

Figure 5. *Five Different pass-band Gaussian-filtered applied on two octaves giving different scales.*

The BEMD-based SIFT algorithm apply the BEMD on the obtained scales in Fig.5 to compute their first IMFs as it is shown in Fig.6.

The extrema elements of the obtained first IMFs for each scale is a detail of pure oscillating mono-component to be matched/detected on the first IMF's extrema elements of the analyzed image.

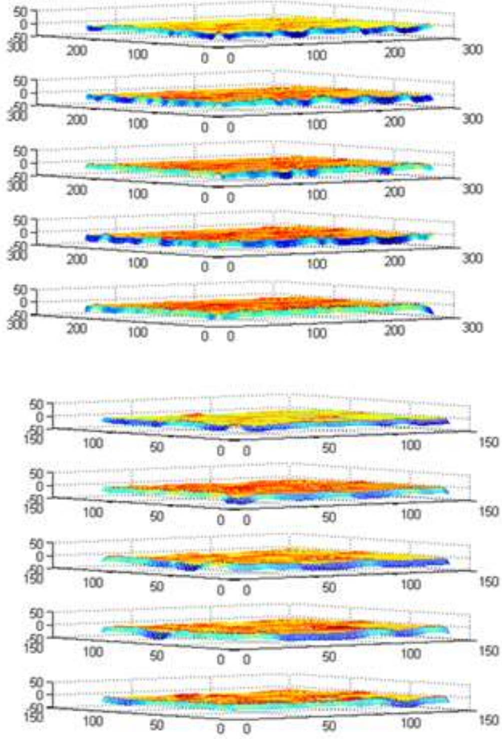

Figure 6. *First IMFs of each Gaussian-filtered scale: (a) The first IMFs of the octave 0 scales, (b) The first IMFs of the octave 1 scales.*

5. BEMD-based Scale-Invariant-Features-Transform applied to road safety application:

In this section, we apply the proposed BEMD-based Scale-Invariant-Features-Transform to detect signs of speed limitation. Then, in accordance with the detected sign, the motion vector magnitude threshold used to track only the speeding vehicles can be then automatically defined for the KLT algorithm (*Kanade-Lucas-Tomasi*).
Fig.7 shows the image to be analyzed and a template for a limitation speed sign of 80km/h to be detected.

Figure 7.*Template to be detected in (a) and the image (frame) to be analyzed in (b).*

Fig.8 shows two octaves on which the Gauss filter was applied for different bands (different cut-off frequencies) to obtain five different scales for each octave.

Figure 8. *Five scales of two octaves for the template.*

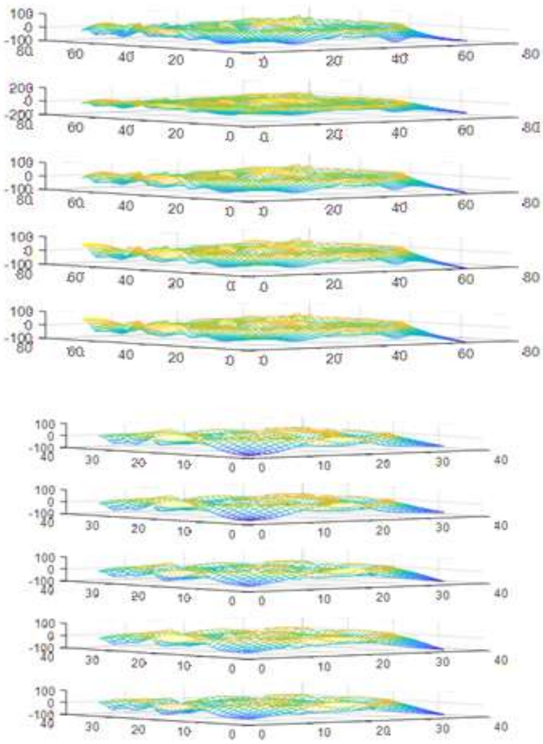

Figure 9.*The first IMFs obtained by applying BEMD on scales of fig.8: (a) 1st octave k=0, (b) 2nd octave k=1.*

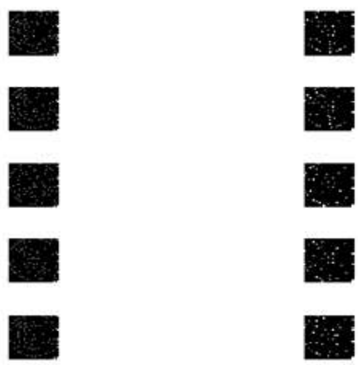

Figure 10.*The first IMF's extrema matrixes of the different scales obtained in Fig.9: (a) the 1st octave extrema matrixes, (b) the 2nd octave extrema matrixes.*

The BEMD-based Scale-Invariant-Features-Transform apply the improved BEMD [28] on the different scales to obtain their 1st IMFs and consider their extrema elements to be the invariant components for their interested characteristics (the finest details with locally zero mean values and oscillatory mono-components free from any continuous component).
Fig.9 shows the 1st IMFs of the different scales of the two octaves obtained in the fig.8.
Fig.11 shows the 1st IMF and its extrema matrix of the analyzed image on which the extrema matrixes of the different 1st IMFs of the different scales will be searched to be detected where the spatial location of the obtained detection will be the same on the analyzed image.

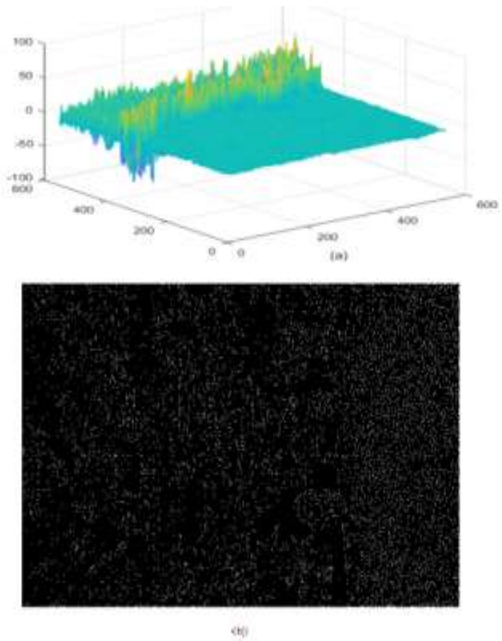

Figure 11.*The first IMF's extrema matrix obtained by applying improved BEMD [28] on the analyzed image of Fig.7-b: (a) the 1st IMF in 3D representation, (b) the 1st IMF's extrema matrix.*

Figure 12*. Detected and recognized sign using the proposed BEMD-based Scale-Invariant-Features-Transform.*

The result obtained by searching for the matrixes of extrema elements of the different 1st IMFs of the different scales (Fig.10) on the 1st IMF's extrema matrix of the analyzed image (Fig.11) is given on Fig.12 where the spatial location of the obtained detection is the same on the analyzed image.
After detecting and recognizing the prohibitory traffic signs for speed limitation (Fig.12), the motion vector magnitude threshold for the KLT algorithm will be automatically defined and so the speeding vehicle will be tracked.

5.1 Calibration:

Before applying the KLT algorithm for speeding vehicles tracking, the unities km/h and pixel/frame should be firstly matched. This step is called the calibration.
After calibration using a cross-bar of pre-known and apparent length in the video (analyzed frame). The real length of the pixel is calculated by calculating the number of pixels in the cross-bar length using the Pythagorean theorem. Then, knowing the total duration of the video and the number of its frames, the time of a frame is calculated. Finally, the number of pixels per frame corresponding to the limit speed of the detected sign is deduced. This makes it possible to define exactly the threshold magnitude of the motion vectors to be considered for tracking by the KLT algorithm.

5.2 KLT algorithm:

The Kanade-Lucas-Tomasi (KLT) Feature Tracker algorithm estimates the 2D translation and scale changes of an image template between original template coordinates and a given reference image using the Inverse Compositional algorithm [29].The optical flow method calculates pixel movement between frames over time (Fig.13) [31]. Optical flow can track the motion of each pixel in the image. The calculation used for all pixels is dense optical flow and for some pixels, it uses the sparse optical flow method. KLT is a representative sparse optical flow algorithm for the feature tracking process. We use this method to trace the points that have been formed in each sequence frame. The grayscale value of the same spatial point pixel does not change in all frames. It is called constant grayscale values which are used to assume the optical flow method. Figure 5 explains that when a pixel in position (x, y) at time t moves to the position $(x + dx, y + dy)$ at time $t + dt$, the grayscale values of the two pixels are same [30].

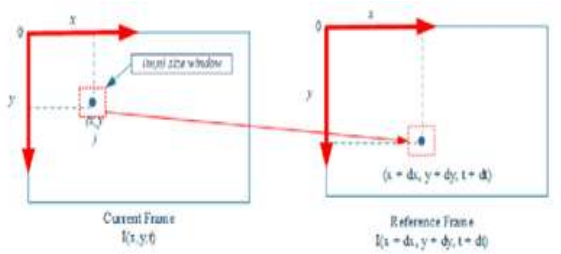

Figure 13.*Synoptic scheme for Kanade Lucas Tomasi (KLT) feature tracking algorithm [31].*

5.3 The KLT algorithm applied to track speeding vehicle using the automatically computed magnitude threshold for the motion vector throw the limit speed sign detection:

The following figure illustrates the tracking of speeding vehicles by the KLT algorithm after setting the speed limit by detecting the speed limitation sign using the SIFT algorithm based on the BEMD proposed in [28] which allowed to automatically set the threshold of the motion vectors (blue vectors on the following figures) for the KLT tracking algorithm.

Figure 14. *Plot of optical flow vectors on a representative video frame for tracked speeding vehicles by KLT algorithm referring to the limit speed sign detection and recognizing using the proposed BEMD-based Scale-Invariant-Features-Transform.*

The following link shows a registration for the speeding vehicles tracking by KLT algorithm using the automatically computed magnitude threshold, for motion vectors, in concordance with the limitation speed sign recognizing using the proposed BEMD-BASED SCALE-INVARIANT-FEATURES-TRANSFORM:

6. Conclusions

In this paper, an efficient object detection method using BEMD-based Scale-Invariant-Features-Transform is proposed and applied in road safety.

Firstly in this paper, we propose a new efficient BEMD-based SIFT algorithm for object detection. The shown examples illustrate that this algorithm gives correct detection in various conditions. In addition, this algorithm is computationally fast and can be used to quickly detect objects in massive volume of data such as videos. These two advantages for BEMD-based SIFT algorithm are mainly due to:

- On the one hand, the sifting process of the used improved BEMD is based on the image minimums and maximums extraction that gives oscillating mono-components (locally close to a sinusoid). The IMFs can be then considered as the invariant details avoiding an extra time for invariant details searching across each scale's details. In addition, the BEMD sifting can be stopped once the first IMF is computed since it contains the finest details. For these two reasons, the BEMD-based SIFT is computationally fast.
- On the other hand, being pure details (oscillating mono-components with zero mean values), the IMFs don't contain the continuous component, that is sifted in the residue component, and can be then easily detected independently to the object gray scale or colour neither to the various illumination conditions. For this reason, the proposed algorithm gives correct detection in various conditions, such as random blurred images and rotated objects.

Secondly in this paper, the proposed detection algorithm based on the used improved BEMD is applied to recognise the prohibitory traffic signs especially for speed limitation. Then, this recognizing of limit speed signs allowed to automatically define a magnitude threshold for motion vectors in the KLT algorithm for the speeding vehicle tracking.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper
- **Acknowledgement:** The authors declare that they have nobody or no-company to acknowledge.
- **Author contributions:** The authors declare that they have equal right on this paper.
- **Funding information:** The authors declare that there is no funding to be acknowledged.

- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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