A study on detecting and classifying underwater mine like objects using image processing techniques

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ABSTRACT

Detection and classification of underwater mines among natural formations and debris along the sea floor is a tedious task. In order to overcome such scenario an automated computer aided detection and classification system is required. Image processing techniques are used to improve the performance of mine hunting operations using sector-scan, side-scan, magnetometers, cameras, etc. This paper serve as a strategic review of the potential for image processing techniques to aid the detection and classification of underwater mines and mine-like objects in side scan sonar imagery. Five basic components of any Computer-Aided Detection and Classification (CAD/CAC) technique are considered namely image preprocessing, segmentation, feature extraction, computer aided detection and computer aided classification. In this paper more than thirty research papers of image processing techniques are clearly reviewed.

Key words - Underwater mines, Side scan sonar, segmentation, computer aided detection and computer aided classification.

1. Introduction:

Mines are a major threat to the fleet. Finding and clearing minefields under the water is an extremely important but difficult task. In response, systems have been produced to scan the sea floor for mines. Detecting and classifying mines among natural formations and man-made debris along the sea floor can be a difficult task. To reduce the operator dependency an automated computer aided detection and classification system is reviewed.

The heavy human reliance on visual information has made human beings highly skilled at the detection and classification of objects in images. Despite human expertise at comprehending visual information, sonar imagery still presents many challenges since it lies outside the normal scope of human visual experience.

One of the many tasks an Unmanned Underwater Vehicle will perform is the location of stationary targets. Depending on the specific targets, many different sensors can be used to perform this task. Side Scan Sonar (SSS) is high resolution active sonar which has been used successfully for the location of targets on or near the seafloor.

This paper is structured into a number of sections. Section 2 presents the system overview, Section 3 explain about side scan sonar images, Section 4 describes the image preprocessing, Section 5 contains the segmentation, Section 6 describes the feature extraction, and Section 7 presents computer aided detection, Section 8 summarize the computer aided classification and Section 9 concludes the paper.

More recent approaches have utilized a number of complex image processing techniques to improve on this. B. R. Calder, L.M. Linnet, and D. R. Carmichael [7] employed a technique based on successive-approximation vector quantization and simple nearest-neighbor technique for classification. Chinmay Rao, Kushal Mukherjee , Shalabh Gupta, Asok Ray and Shashi Phoha [12] have considered data-driven symbolic dynamic based method to detect mine like objects. G.J.Dobeck, J.C.Hyland and L.Smedley [19] used Support Vector Machine (SVM) classifier to classify the same. Benoit Zen, Gilles Mailfert, Alain BerthoIom, Heme Ayreault [20] utilized Fuzzy relaxation algorithm and Kalman filter for image preprocessing steps. Rebecca T. Quintal, John E. Kiernan, John Shannon Byrne, Paul S [21] examined Dysart Automatic Contact Detection (ACD) algorithm to detect the objects.

Esther Dura, Yan Zhang, Xuejun Liao, Gerald J. Dobeck, and Lawrence Carin [22] used Kernel-based classifier to classify mine like objects. U. Hoelscher -Hoebing and D. Kraus [23] used Expectation Maximization (EM) algorithm to extract specified features in side scan sonar image. E. Coiras, P.-Y. Mignotte, Y. Petillot, J. Bell and K. Lebart [24] employed the central filters for feature extraction. Ai Ling Chew, Poh Bee Tong, Chin Swee Chia [26] examined adaptive threshold segmentation technique to segment the side scan sonar images and Self-adaptive power filtering technique for image preprocessing steps. Esther Dura, Judith Bell [29] have considered unsupervised Markovian segmentation algorithm to segment the image. J. Bell, Y. Petillot, K. Lebart, P.Y. Mignotte, E. Coiras and H. Rohou [31] have considered Dempster-Shafer Theory for classification.

2. System overview:

The main task taken is examining image-processing techniques tailored for side scan sonar imagery. The image processing techniques consider in this task can be grouped into five categories as given in Fig-1:

The main part of **Image preprocessing** stage is clutter suppression and image enhancement, and its purpose is to normalize the background throughout the image. **Segmentation** refers to the process of partitioning a digital image into multiple segments. Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images. In **feature extraction,** when the input data given to an algorithm is too large to be processed and it is suspected to be notoriously redundant (much data, but not much information) then the input data will be transformed into a reduced representation set of features. Transforming the input data into the set of features is called feature extraction. **Computer aided detection (CAD)** techniques may be useful to detect mine like objects in side scan sonar imagery. Confirmation of whether the object is actually a mine and its specific type are left to the human operator or subsequent processing methods. **Computer aided classification (CAC)** techniques may be able to positively identify a mine-like object as a mine and determine the type and orientation of the mine involved. Fig-1 represents the cycle of image processing techniques involved in clarifying the mine like objects.

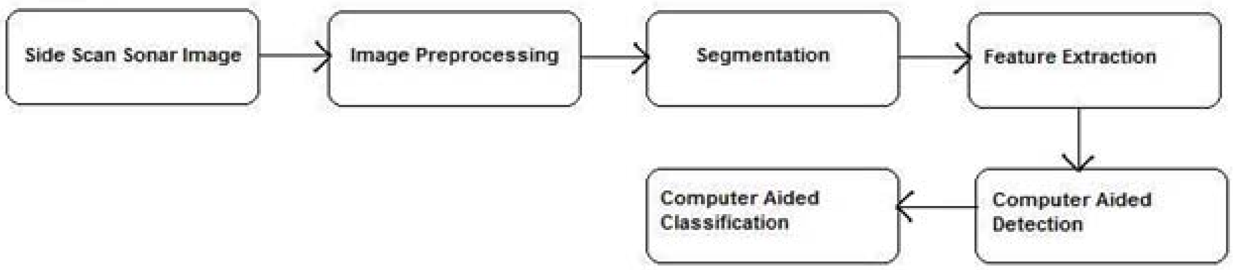

Fig. 1: Image processing techniques

The above grouping is only a rough guide to image processing techniques, as a great deal of overlap is often found, and some techniques defy being grouped in this way. The following sections describes about the above image processing techniques.

3. Side Scan Sonar (SSS):

This section examines the image processing techniques that may enhance the utility of side-scan sonar systems for underwater mine applications.

A major interest of high-resolution sonar images is natural or artificial objects detection on the sea-bottom. Once processed, these images give information about the object shape, texture and identity. Unmanned Underwater Vehicle (UUV) is equipped with a SSS for searching and mapping missions. Each SSS return provides a narrow view of the bottom. Therefore, the sonar must be swept over an area of interest in order to locate targets. Because a single return is not easily interpreted by a human operator, sequential returns are plotted on a strip chart in order to create a "picture" of the seafloor. Then the operator interprets the picture to detect and classify targets [10] [13].

Sonar images consist of three kinds of information:

- Echo: high gray level pixels resulting from the reflection of the emitted wave on an object
- Shadow: low gray level pixels due to the reflected wave absence behind an obstacle (object, rocks, sea-bottom relief ...)
- Reverberation: pixels being neither an echo nor a shadow. They represent acoustic waves backscattered by the sea-bottom [13].

Unmanned underwater vehicles (UUV) are a key technology in reducing the dangerous work of surveying and clearing underwater mine fields. Side-scan sonar is the sensor of choice on many of today's UUVs because of its mature high-resolution imaging capability [5].

4. Image Preprocessing:

Clutter suppression and image enhancement, which is a main part of this task normalizes the background throughout the image to a constant level, so that highlight and shadow levels are consistent and clearly stand out. Enhancement techniques that have the potential to enhance the contrast of mine-like objects in sonar images Examples of this are the removal of noise and clutter, background normalization, and the processing of sonar imagery to make best use of available knowledge of the human visual system.

Quidu, J. Ph. Malkasse, G. Burel and P. Vilbe, proposed an approach based on a hybrid set of descriptors in the year of 2000. Before evaluating the features, image data are preprocessed in order to obtain a binary image and to improve the robustness of the features. In noise reduction, irregularities of the outer boundary of the shadow may have undesired effects on the recognition system. While preserving the global information of the shadow, it is aimed to smooth the boundary. The shadow's closed boundary can be represented by a periodic function of the contour coordinates. By computing **Fourier descriptors** and removing the high frequencies, the new shadow will become smoother than the original one. To improve robustness of topological features, image normalization is performed. It has to provide a new image as it would be seen under a grazing angle of 45 degrees preserving shadow ratios [15].

The pre-processing block contains pre-normalization, clipping and data decimation blocks. Normalization reduces data non-homogeneity. A combination of **feed-forward and backward normalizer** was employed, which computes water column information and was developed by Gerry Dobeck [16] in 2000.

T.Aridgides, M.Ferdandez and G.Dobeck proposed the **Adaptive Clutter Filtering (ACF)** algorithm for image preprocessing in the year of 2001. After normalization, data clipping better conditions the data for ACF processing, by resulting in a more stable target signature for the algorithm design and application [2]. The ACF is a multi-dimensional adaptive linear **FIR (**finite impulse response**)** filter, optimal in the LS (least-square) sense that is applied to low-resolution data. It performs simultaneous background clutter suppression and peak target preservation by exploiting differences between clutter and target correlation characteristics. In its latest version a 1-dimensional range only ACF, which was matched to both average highlight and shadow target shape information (computed a-priori using training set data), was applied after mean removal. The ACF block output is processed through a cross range domain, whole column, global normalizer, which employs negative and small value data clipping and removes any remaining non-stationarities in the data [2].

S.Reed, Y.Petillot and J.Bell are also involved with ACF implementation for image preprocessing in 2003. The analysis of side scan sonar images in the field of mine countermeasures is traditionally carried out by a skilled human operator. This analysis is difficult due to the large variability in the appearance of the side scan images as well as the high levels of noise usually present in the images. With the advances in autonomous underwater vehicle technology, automated techniques are now required to replace the operator to carry out this analysis on-board. Adaptive Clutter Filter technology is used to suppress the background clutter after which classification is carried out on an optimum set of features [3].

5. Segmentation:

For side-scan sonar images, segmentation is often used to separately classify pixels as belonging to highlights, background, or shadow regions before higher level CAD/CAC techniques are used to search for mine-like objects. After each pixel has been classified into one of the three choices, the pixels are often clustered together with their neighbors to remove incorrectly classified pixels. There exists a large variety of image processing techniques for segmentation and many of these have been applied to this problem.

S.Reed, Y.Petillot and J.Bell used Markov random field (MRF) for segmentation in the year of 2003. MRF models have been used to segment noisy images in a variety of applications. This success is due to their ability to consider spatial information within the image as well as their ability to model a priori information. The model described here segments the raw sonar image into regions of object-highlight, shadow and background. Priors were added to the MRF framework which modeled the characteristic mine signature in Side scan sonar. These priors ensured that any object-highlight regions were therefore of the correct size and that they were accompanied by a shadow region (objects in side scan imagery generally appear as a highlight/shadow pair) [4].

F. Langner, C. Knauer, W. Jans and A. Ebert proposed some of the segmentation algorithms in 2009. Segmentation algorithm using neighborhood information is done by performing threshold segmentation based on a higher order histogram. Each neighbor pixel is represented by a new dimension in such a histogram. This technique leads to fast segmentation for acoustic images since, in principle, resolution of the image is reduced by using the neighborhood for segmentation. Compared to normal threshold segmentation, the image generated by the segmentation algorithm using neighborhood information contains much less noise. Selecting regions of interests **(**ROI) after segmentation depends on the existence of highlight **–** shadow pairs. Using a broader data set for testing, this screening method has shown quite good performance for detecting MLOs [14].

C.M.Ciany and J.Huang involved in adapting the image segmentation for side scan sonar images in the year of 2000. Here in image segmentation, the digitized side scan sonar image is median filtered to reduce speckle. The image is then split into overlapping range segments ("sub frames"), each of which is adaptively thresholded (via pixel histograms) to identify Highlight (high pixel values), Shadow (low pixel values), and Background (remaining pixels) pixel types [1][6].

JoEllen Wilbur, Robert J. McDonald and Jason stack segmented side scan images using kernel based classifier in 2009. Contourlets effectively model the contours and ridges in an image. The lattice structure breaks the image into multi resolutions, or multi-scales. Each scale is then grouped into contour segments using a set of skewing operations that form the mathematical equivalent of placing a directional filter bank on each output of the lattice. Grouping of the coefficients into contour segments gives rise to dominance of the contourlet coefficients along contours and ridges in the image. When the wavelet distinguishes point singularities and effectively acts to separate point singularities at discrete levels, the contourlet separates contour edges across scales [9].

M. Neumann, C. Knauer, B. Nolte, W. Jans and A. Ebert used an iterative segmentation algorithm in the year of 2008. Iterative segmentation process is carried out in order to separate the image into shadow and background. This segmentation is based on an energy function that combines the local neighborhood segment information and the amplitude of a pixel. By minimizing this function, a clear shadow, the most significant target characteristic can be extracted. The ROI (region of interest) is segmented by an iterative algorithm using fuzzy functions into highlight, back ground and shadow. For detection of manmade objects, the shadow is the most interesting of the image. Many studies are dealing with an automatic extraction of object shadow. Simple approaches use good results on gravel ground. For bumpy seabed containing silt or rocks other methods with local thresholds are more promising. The main disadvantage of all threshold based variations is poor robustness against speckle and a dark shadow pixel cannot be found only in pixel's color. Since SSS images are typically very noisy, some segmentation approaches exploit the type of noise (its specific statistical properties) with Markov Random Field concepts [18].

6. Feature Extraction:

Feature extraction involves simplifying the amount of resources required to describe a large set of data accurately. When performing analysis of complex data one of the major problems stems from the number of variables involved. Analysis with a large number of variables generally requires a large amount of memory and computation power or a classification algorithm which over fits the training sample and generalizes poorly to new samples. Feature extraction is a general term for methods of constructing combinations of the variables to get around these problems while still describing the data with sufficient accuracy.

S.Reed, Y.Petillot and J.Bell examined the Co-operating Statistical Snake (CSS) model in 2003, Man-made objects such as mines leave regular-shaped recognizable shadow regions in Side scan imagery. These shadow regions allow the object to be classified. Shadow extraction techniques have been developed that work well on simple seafloors but provide poor results on more complex backgrounds. The Co-operating Statistical Snake (CSS) model overcomes these limitations by extracting both the object-highlight and shadow regions which are strongly related [4]. The CSS model considers a mugshot of each detected MLO and assumes the image to be composed of an object highlight, object-shadow and background region. A fast, multi-scale segmentation technique is used, which segments by considering the image statistics. To ensure accurate segmentation on complex seafloors, priors were added modeling the relationship between the object highlight and object-shadow regions [4]. As well as being capable of obtaining accurate extraction results on complex seafloors, the CSS model was also capable of identifying and removing false alarms. Detected MLO regions which did not have a highlight and shadow pair would often result in the CSS snakes expanding past mine-like dimensions. When this occurred, the false alarm could be removed from the result [4].

Jie Tian and Chunhua Zhang proposed an advanced algorithm for feature extraction in the year of 2004. Features are those items which uniquely describe a target, such as size, shape, composition, location, and whether the target is on the bottom or in the water column. Simple geometric calculations determine a target's size and shape. Using the UUV's navigation data, a determination of the location of the target can be performed. The relative location of the target's shadow determines whether the object is on the bottom or in the water column. In feature extraction the highlight shadow pixels of each image segment are geometrically associated to contiguous highlight shadow regions of interest, each of which are processed to extract key signal, Signal-to-Noise Ratio (SNR), and geometric shape features (e.g. area, perimeter) [8].

Chinmay Rao, Kushal Mukherjee, Shalabh Gupta, Asok Ray and Shashi Phoha used a geometric model to extract the features from side scan sonar images in 2009. This model has been used for feature extraction to detect and classify mines in a sonar trace. This model is used in the training set to obtain the distributions of the various regions of a mine. A sequence of tests is determined to characterize a mine according to the identified distributions. Based on the principles of side scan sonar operation and properties of sound wave propagation in the oceans, a mine is characterized by three distinct regions that correspond to a bright spot, a shadow and the clutter around both bright spot and shadow [13].

The feature extraction subsystem correlates a shadow with a target if the shadow's along track dimension is equal to the targets along track dimension, and the shadow's cross track position is greater than the target's cross track position. In order to correctly determine a target's size, the relationships of a target and its shadow must be utilized. If a target has no shadow, then the actual size, as opposed to the slant-range size, cannot be determined.

Anthony R. Castellano and Brian C. Gray developed the feature extraction subsystem to extract features in slant-range space. In many cases, a target may not have a detectable shadow associated with it because of reverberation, multipath and side-lobe effects. In addition, the SSS may pass the target at a vertical angle of approximately 90° causing little or no shadow. For these reasons, the authors developed the feature extraction subsystem. The target's shadow is only used to determine if a target lies on the bottom or in the water column. If a shadow has been correlated with a target and it is disjoint from the target, then the target is in the water column. Otherwise, the target is assumed to be on the bottom. Geometric features are computed by determining the targets centroid, using the slant-range data provided by the detection subsystem [10].

7. Computer Aided Detection (CAD):

A wide variety of techniques have been used in the literature to attempt to detect mine like objects in side-scan sonar imagery. The detection, whose purpose is to realize the apartment of target-like objects and background, is the basis of the further classification.

S.Reed, Y.Petillot and J.Bell used the Markov Random Field (MRF) to carry out a detection-oriented segmentation on the raw side scan image in the year of 2003. Most detection models consider the underlying label field use a two-tier process (the image is first segmented after which the detection problem is considered). The model has been tested on real and synthetic images, both of which contained clutter and a variety of seabed types. This model will directly segment the image into regions of object-highlight, sea bottom reverberation, and shadow using available a priori spatial information on the appearance of mine signatures in side scan sonar. Results will then be presented on both real and synthetic images [3] [4].

Anthony R. Castellano and Brian C. Gray developed a detection subsystem to detect the mine like objects in side scan sonar image. This system must isolate the parts of a return that contain possible objects, where an object is defined as a target or its acoustic shadow. This subsystem utilizes power thresholding and median filtering to reduce a single return into targets, shadows, and a uniform background. This is followed by an accumulator that constructs entire objects from individual returns. Although the thresholding correctly detects targets and shadows, it also produces spurious detections because of variance in the background. These spurious detections are impulsive in nature. In order to reduce false detections without eliminating true detections, the output of the thresholding is followed by a two dimensional CxD recursive median filter, where C is the along-track size in returns and D is the across-track size in sample points. It has been shown that a median filter eliminates impulse noise with minimal distortion of large objects (with respect to the filter size) and hard edges. Further, a recursive median filter will reduce the thresholded return to a root signal in one pass [10].

Guo and Szymczak (1998) used the wavelet transform to decompose a side-scan image into a number of different channels. The image of an object in each channel then forms features for a neural network classifier. The neural network classifier uses a set of sub networks, each examining a different wavelet channel. This forms an interesting multi-resolution. Neural network detects mine-like objects based on features at various different resolutions. This concept is probably an important component of human visual detection and classification, and may be an useful research direction [17] [28].

8. Computer Aided Classification (CAC):

High resolution sonar provides high-quality acoustic images of the sea-bed, allowing the classification of objects from their cast shadow. After the segmentation step, a set of features is extracted from the shadow.

S.Reed, Y.Petillot and J.Bell used the Fawcett technique for computer aided classification in 2003. Fawcett has attempted this form of classification using simple features drawn from a mug shot of the object (this process assumed prior detection of the object). The technique is interesting but yet was tested using only synthetic data where the success rate deteriorated when complex backgrounds where added to the object mug shots. The extracted highlight region of the object has also been considered for classification but is usually too variable and dependent on the specific sonar conditions to be used as a reliable classification feature. A popular feature to use is the object's shadow region which is generally more dependable and can be used to accurately classify the object if it can be extracted accurately [3].
Chinmay Rao, Kushal Mukherjee , Shalabh Gupta, Asok Ray and Shashi Phoha proposed the Sonar simulator model for classification process in 2009. A sonar simulator model considers different possible object shapes, measuring the plausibility of each match. The simulator allows possible shapes to be viewed under the same sonar conditions as the unknown MLO was detected. In Dempster-Shafer theory, A final classification decision is carried out using Dempster-Shafer theory which allows both mono-image and multi-image classification [4].

F. Langner, C. Knauer, W. Jans and A. Ebert used the Probabilistic Neural Network (PNN) algorithm for classification in the year of 2009. Currently the PNN is used in the Classification subsystem because of limited training data. The PNN is a multi-layer feed-forward network which uses sums of Gaussian distributions to estimate the probability density function (PDF) for a training set. This trained network can then be used to classify new data sets based on the learned PDF, and further, to provide a probability factor associated with each class. It has been shown that a neural network based on estimates of PDFs is capable of rapid learning of pattern data and mapping to any number of classifications. The PNN computes nonlinear decision boundaries between classes [10] [14].

C. M. Ciany and W. Zurawski proposed the fusion algorithm for classifying mine like objects in side scan sonar image in 2001. Fusion algorithm combines of outputs from multiple CAD/CAC algorithms. Several fusion methods have been developed and applied to side scan sonar test data in conjunction with the CAD/CAC adaptation to the VSW environment. The fusion methods were originally demonstrated on data from the VSW environment using three CAD/CAC algorithms from Raytheon, CSS and Lockheed Martin. The Raytheon and CSS CAD/CAC algorithms were subsequently applied to the shallow-water environment. Since the three CAD/CAC algorithms use very different approaches, assumption have been made that valid classifications are near to each other and false alarms occur randomly in the image. The resultant geometric clustering eliminates most of the false alarms while maintaining a high level of correct classification performance [6].
The data fusion processing, consists of two principal functions: **Geometric Clustering** of the classified contacts from the multiple classifier outputs that groups individually classified contacts together when the distance between them is less than a prescribed threshold. **Cluster Thresholding,** in which the target confidence levels associated with clustered contacts are processed and then compared to a threshold for final classification [6].

TABLE I. Observation and Analysis on Existing System

Author	Year	Image Preprocessing	Segmentation	Feature Extraction	Detection	Classification	Finding Rate
C.M.Cian,y J.Huan	2000	Median filter	Adaptively threshold technology	Key Signal, Signal-to-Noise Ratio (SNR), and geometric shape features	Geometric clustering, Cluster confidence factor thresholding	Thresholding of the weighted scores.	75%
C. M. Ciany and W.Zurawski	2001	Median filter	Adaptively threshold technology	Key Signal, Signal-to-Noise Ratio (SNR), and geometric shape features	Geometric Clustering, Cluster Thresholding Algorithms	Fisher-Based Fusion Algorithm	83.5%
B. R. Calder, L.M. Linnet, and D. R. Carmichael	1998	Likelihood function	Texture segmentation method	Markov chain Monte Carlo (MCMC) system	Bayesian methods	Successive-Approximation Vector Quantization, Simple nearest-Neighbor Classification	87%
Jie Tian and Chunhua Zhang	2004	Nonlinear matched filter	Threshold Segmentation	_	Sliding Match Mask Technique	Support Vector Machine (SVM) classifier	87.4%
Chinmay Rao , Kushal Mukherjee , Shalabh Gupta, Asok Ray and Shashi Phoha	2009	Symbolic Analysis	Traditional partitioning techniques	Geometric Model and Markov machine Technique	Data-driven symbolic dynamic based Method	Threshold-Based Classification	91.5%
M.Neumann, C. Knauer, B. Nolte, W. Jans and A. Ebert	2008	Prior Detection Algorithm	Markov Random Field (MRF) model, Fast iterative Segmentation Algorithm	Hough Transform Algorithm	Region of interest and Shadow contour	Robust Classification Approach(Combination of fuzzy function)	100%
Ai Ling Chew, Poh Bee Tong, Chin Swee Chia	2007	Self-adaptive Power filtering technique	Adaptive threshold Segmentation technique	Moore Neighborhood Tracing algorithm	2D Fourier Transforms	Divide and conquer approach.	80%

Table I illustrates the type of methods which had been used in the various stages of image processing in the existing systems and shows that the finding rate of the methods ranges from 75% to 100%.

9. Conclusion:

This paper has examined various image processing techniques which have the potential to aid the detection and classification of mine-like objects in side scan sonar imagery. In side scan sonar-imaging applications, five components of Computer-Aided Detection and Classification (CADCAC) system are examined. These components are Image preprocessing, Segmentation, Feature extraction, Computer-Aided Detection and Computer-Aided Classification. For each of these components, image processing techniques with the potential to improve the performance of underwater mine side scan sonar systems were discussed, and examples of successful or instructive methods from the literature were given. Finally, some general image processing considerations common to each imaging methodology were given. Table I present the selected overview of image processing techniques among the existing systems and also display the finding rate of mine detection. The need of human element of the mine hunting system is emphasized.

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