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RESEARCH ARTICLE

# An Automated Local Binary Pattern Ship Identification Method by Using Sound

## Ses Kullanarak Otomatik Yerel İkili Model Yöntemi ile Gemi Tanımlama

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**ABSTRACT**

Sound classification is one of the most important areas of research for mechanics and applied computer sciences. Using the sound classification method, many biometric applications/methods have been presented in the literature. This study presents a ship identification method using sounds. The method presented here is very simple and effective. It has only two fundamental phases and these are feature extraction by one dimensional binary pattern (1D-BP) and classification with conventional classifiers phases. 1D-BP extracts 256 features from each sound and these sounds are forwarded to classifiers. To test this ultra-lightweight sound identification method, a ship sounds dataset was collected from YouTube. According to our results, this method achieved a 97% classification accuracy. This result clearly demonstrates the merits of the 1D-BP based on ship sound classification method and the sound-based ship identification method which we present here.

**Keywords:** Ship identification by using sound, 1D-BP, Classification, Sound processing, Machine Learning

**ÖZ**

Ses sınıflaması, makine öğrenimi ve uygulamalı bilgisayar bilimleri için en önemli araştırma konularından biridir. Ses sınıflandırma yöntemi kullanılarak literatürde birçok biyometrik uygulama / yöntem sunulmuştur. Bu çalışma sesleri kullanarak bir gemi tanımlama yöntemi sunmaktadır. Sunulan bu yöntem çok basit ve etkilidir. Bu yöntemin sadece iki temel fazı vardır ve bu fazlar, bir boyutlu ikili örüntü (1D-BP) ile özellik çıkarma ve geleneksel sınıflandırıcı fazlarla sınıflandırmadır. 1D-BP her sesten 256 özellik çıkarır ve bu sesler sınıflandırıcılara iletilir. Bu ultra hafif ses tanımlama yöntemini test etmek için YouTube'dan bir gemi sesleri veri kümesi toplandı. Sonuçlara göre, bu yöntem %97 sınıflandırma doğruluğu elde etmiştir. Bu sonuçlar, gemi ses sınıflandırması ve ses tabanlı gemi tanımlaması üzerine sunulan 1D-BP tabanlı yöntemin değerini açıkça göstermiştir.

**Anahtar kelimeler:** Ses kullanarak gemi tanımlama, 1D-BP, Sınıflandırma, Ses işleme, Makine Öğrenmesi

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## 1. INTRODUCTION

Sound classification and sound processing are two of the most basic and essential areas in mechanics. The popularity of voice analysis is increasing, especially considering the size and diversity of data collected with the development of the internet and information systems. The presence of mobile phones is visible to almost everyone, showing that voice and video recording has become more accessible. With the increasing interest in sound analysis over the years, its use has become widespread in many different fields such as disease recognition (Badem, 2019), warning recognition (Çalik et al., 2015), vehicle recognition (George et al., 2013) event recognition (Mesaros, Heittola & Virtanen, 2016), gun recognition (Khan, Divakaran & Sawhney, 2009). In general, sound analysis consists of collecting a data set, establishing a classification process, separating the data set into training and test, extracting features, selecting features, representing the selected features for the classifier, applying the classifier algorithm, and evaluating the performance of the classifier model. One of the essential elements in sound classification is the removal of features (Liang & Nartimo, 1998). As a result of changing the methods used, sound classification success can be improved. Many different methods such as SVM (Wang et al., 2006), kNN (Chen et al., 2015), multilayer perceptron (Gupta, et al., 2007), random forest (Togneri, Sohel & Huang, 2017), decision tree (Romero, Luque & Carrasco, 2017) are used in sound classification.

## 2. CONTRIBUTIONS

When building seafaring vessels, one of the most essential issues is ensuring that the vessel makes as low a noise as possible. This is because ship detection is one of the crucial methods for safety. This importance is better understood when we consider that submarines try to recognize other vehicles only from the sound they make. Although the engine characteristics of each of the watercraft differ, there are efforts to reduce the noise made by the engines. Failure of these engines to meet specific noise standards can cause adverse effects on marine organisms and may produce underwater acoustic radiation that can damage the marine ecological balance (Williams et al., 2015; Farcas, Thompson & Merchant, 2016). Each ship has its own characteristic sound and it can be quite challenging to distinguish these sounds by the human ear. By using the unique sounds/noise of the ship, the ship detection model can be created and these sounds can be utilized as identification data of the ships like biometrics. In addition, knowing the usual typical sound of the ship can alert engineers to the existence of a possible malfunction if an unusual sound is heard. Overall, our main contributions to this field are:

- There are many vehicles which are used on a daily basis, and these vehicles must be identified in some way. The two most used identification methods are image processing and signal processing. Sound processing is one of the signal processing methods, and it is especially valuable for use on ships. We collected a ship sounds dataset to create a testbed for vehicle sound identification and classification.

- LBP is one of the most frequently used feature generators for images, but the 1D-BP has not been as widely used as LBP, though it has variable merits for signal processing. Therefore, a high accurate ship detection method is presented using 1D-BP feature generator.

## 3. DATASET

Sounds made by different types of ships were downloaded onto YouTube using videos that are open to everyone. These files obtained on different dates were downloaded, and sections were produced for 2 seconds for each ship type. In this way, a total of 1025 files were obtained. Firstly, each audio file was converted to a wav file format. And then, the sounds were carefully listened to in order to ensure that there were no different sounds or noises within the file. It was carefully checked to ensure that the same sound did not repeatedly continue during the fragmentation of the audio files. The WavePad Sound Editor program was used for all these processes. The audio files are stored at https://websiteyonetimi.ahievran.edu.tr/_Dosyalar/Genel/5aa50bab-f769-4aad-bca4-9a160cae898b-b265eb3e-d962-46ee-998b-e28ebf8894ed.rar for use by other researchers. In Table 1 below, the details of the number of sounds formed are listed.

Table 1.
*Type and Number of Ship Sounds*

| ID | Ship Type | Number of Observations |
|---|---|---|
| 1 | Small Craft | 77 |
| 2 | Pirate Ship | 117 |
| 3 | Cruise Ship | 119 |
| 4 | Sailing Boat | 117 |
| 5 | Below-Deck Sailboat | 119 |
| 6 | Submarine | 116 |
| 7 | Arctic | 120 |
| 8 | Ferry Boat | 122 |
| 9 | Beach | 118 |
| | Total | 1025 |

## 4. THE PROPOSED 1D-BP BASED SOUND CLASSIFICATION METHOD

In this study, a new generation 1D-BP based ship identification method is presented. The presented method is a simple, cognitive, and lightweight method. The method consists of ship sounds acquisition, feature extraction with one-dimensional local binary pattern (1D-BP), and classification phases. To better understand the proposed 1D-BP based method, a graphical explanation of this method is shown in Fig. 1.

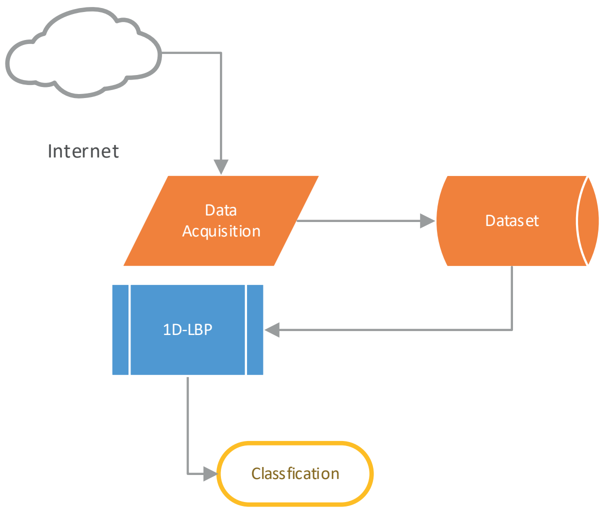


*Figure 1.* Graphical summarization of the 1D-BP based sound classification method

The data acquisition phase was explained in Section 2. The steps of this method are given below.

**Step 0:** Load collected ship sound

**Step 1:** Apply 1D-BP to collected ship sounds and generate 256 features.

In the feature generation phase, 1D-LBP is used as a feature extractor, and it is applied to preprocessed values. Steps of the 1D-LBP are given below.

**Step 1.1:** Divide preprocessed values into *nine* sized overlapping blocks.


*Figure 2.* Demonstration of the used 9 sized overlapping block. In the 1D-LBP, the 5th value is assigned as center value, and bits are extracted using center value and other values together

**Step 1.2:** Extract bits by using center value, other values, and signum function together. The mathematical definition of the signum function is shown in Eq. 1.

$$sgnm(o,d) = \begin{cases} 0, o < d \\ 1, o \geq d \end{cases} \quad (1)$$

where $sgnm(.,.)$ is signum function, $o$ and $d$ are input variables of the signum function. In this work, $o$ is $v_i$ and $d$ is center value.

$$bit_i = sgnm(v_i, center), i = \{1,2,\ldots,8\} \quad (2)$$

**Step 1.3:** Convert decimal number to extracted bits.

$$dcv = \sum_{t=1}^{8} bit_t * 2^{8-t} \quad (3)$$

where $dcv$ is the calculated decimal value using extracted bits.

**Step 1.4:** Create a feature signal using calculated decimal values from each block.

**Step 1.5:** Extract the histogram of the feature signal and obtain features.

An example of 1D-LBP is graphically shown in Fig. 3.

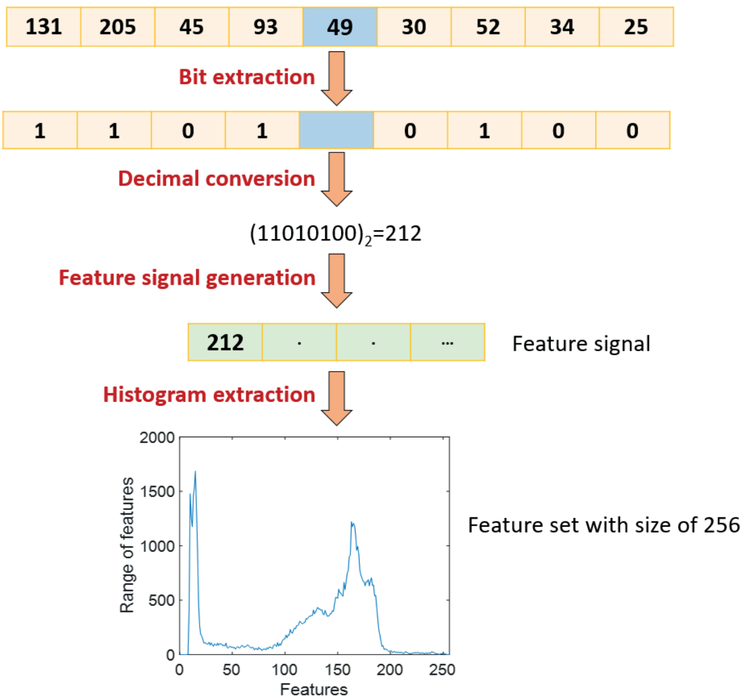


*Figure 3.* Graphical explanation of the 1D-LBP with a numerical example

**Step 2:** Forward extracted features to classifiers and obtain results. In this phase, *four* conventional classifiers are used. The selected classifiers are Decision Tree (DT), k Nearest Neighborhood (kNN), Linear Discriminant Analysis (LDA), and Support Vector Machine (SVM).

**Decision Tree:** DT is one of the most widely used conventional classifiers and the used DT is called Fine Tree. The attributes of the used DT are given below. The number of splits is chosen as 100, Gini is split criterion.

**k Nearest Neighbor:** kNN is a parametric and distance-based classifier. In this work, k is chosen as *one* and the Euclidean distance metric is used.

**Linear Discriminant:** LDA is one of the most frequently used linear classifiers. It is a primary and non-parametric classifier. The used setting of the LDA classifier is given as follows. Full is selected as a covariance structure.

**Support Vector Machine:** SVM is an optimization-based classifier and uses variable kernels. In this study, the cubic kernel ($3^{rd}$-degree polynomial kernel) is selected as an activation function. The attributes of the SVM are selected as 3, Auto, One-vs-One for box constraint level, kernel scale mode, and multiclass method, respectively.

In the test and validation phase, a 10-fold cross-validation is generally used.

## 5. Experimental Results

In this work, a ship sound dataset was used to test the performance of the proposed 1D-BP based text classification method. The 1D-BP was coded on the MATLAB2018a programming environment. We coded 1D-BP as a function, and this function was called a feature generator in the main code. The extracted features were forwarded to MATLAB Classification Learner Toolbox (MCL). MCL has 23 shallow classifiers in the decision tree, discriminant, SVM, kNN, and ensemble categories. Four classifiers were selected to show our test results. Accuracy (*acc*), precision (*pr*), recall (*rec*), F1 score (*f1*), and geometric mean (*gm*) were chosen to obtain numerical performance metrics. The mathematical notations of these performance parameters are shown in Eqs. 4-8.

$$acc = \frac{tps + tns}{tps + tns + fps + fns} \quad (4)$$

$$pr = \frac{tps}{tps + fps} \quad (5)$$

$$rec = \frac{tps}{tps + fns} \quad (6)$$

$$f1 = 2\frac{pr * rec}{pr + rec} \quad (7)$$

$$gm = \sqrt{\frac{tps}{tps + fns} * \frac{tns}{tns + fps}} \quad (8)$$

In the Eqs. 4-8, $tps$, $tns$, $fps$ and $fns$ are true positives, true negatives, false positives, and false negatives, respectively. We also selected *four* conventional classifiers to show the discriminative attribute of the proposed 1D-BP based feature extraction method. The obtained results are listed in Table 2.

Table 2
*Results of the acquired ship sound dataset*

| **Classifier** | $acc$ | $pr$ | $rec$ | $f1$ | $gm$ |
|---|---|---|---|---|---|
| DT | %95.1 | 0.9512 | 0.9523 | 0.9521 | 0.9514 |
| kNN | %95.8 | 0.9580 | 0.9586 | 0.9585 | 0.9576 |
| LD | %94.9 | 0.9493 | 0.9514 | 0.9506 | 0.9494 |
| SVM | %97.5 | 0.9746 | 0.9755 | 0.9752 | 0.9750 |

## 6. DISCUSSIONS AND CONCLUSIONS

In this study a ship sounds dataset and an ultra-lightweight sound classification method for ships is presented. This dataset was collected from YouTube. These sounds were analyzed to block overfitting, and loops were generated. Then, an ultra-lightweight machine learning method was presented. This method is a fundamental method. The collected sounds were directly utilized as the input of the 1D-BP feature generator. The time complexity of the 1D-BP was *O(n)*. This situation clearly demonstrated the lightweight property of this method. These features were forwarded to conventional/shallow classifiers. The advantages gained by this method are given below.

· A novel dataset was collected for ship sound classification.

· We showed discriminative acoustic features of the ships.

· Vehicle identification is essential for applied computer sciences, machine learning, and digital forensics. By proposing this ultra-lightweight sound classification method for ships, the importance of this field is emphasized.

· A high accurate method is presented (See Table 2). The proposed 1D-BP based ultra-lightweight sound classification method also demonstrated success since it achieved high success rates using four-variable classifiers.

X-ying et al. (2010) achieved 94.44% as the highest success rate in ship recognition work with artificial neural networks. Chen et al. (2002), on the other hand, classified the ships from ship sounds by 86.8% using the Probabilistic Neural Network (PNN) method. Yang, Li, and Wang (2002) presented a fractal analysis and wavelet-based vessel volume classification model -and the achieved highest classification accuracy was calculated as 99.23%. Since the data set of the studies here could not be reached, comparisons were not made with the proposed method. Similar studies were carried out with different methods, and different results were obtained. The method used here is very widely used, especially in areas such as face recognition and image classification (Král, Vrba & Lenc, 2019; Hassaballah, Alshazly & Ali, 2019; Wang et al., 2019; Aberni, Boubchir & Daachi, 2020).

In future studies, more datasets could be collected to classify ships or other vehicles. Here, we presented a 1D-BP based ship classification model. Variable textural descriptors and deep learning networks can be applied to the collected new ship sound datasets and variable ship sound classification methods can be presented. Also, new cloud-based or mobile ship monitoring and detection applications can be developed using the proposed model.

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## References

Aberni, Y., Boubchir, L., & Daachi, B. (2020). Palm Vein Recognition based on Competitive Coding Scheme using Multi-scale Local Binary Pattern with Ant Colony Optimization. *Pattern Recognition Letters*, 136, 101-110.

Badem, H. (2019). Parkinson Hastaliğinin Ses Sinyalleri Üzerinden Makine Öğrenmesi Teknikleri ile Tanimlanmasi. *Ömer Halisdemir Üniversitesi Mühendislik Bilimleri Dergisi,* 8(2), 630-637.

Çalik, N., Ata, L. D., Serbes, A., Bolat, B., & Yavuz, E. (2015, May). Performance analysis of feature extraction methods in indoor sound classification. In *2015 23nd Signal Processing and Communications Applications Conference (SIU)* (pp. 2025-2028). IEEE.

Chen, C. H., Huang, W. T., Tan, T. H., Chang, C. C., & Chang, Y. J. (2015). Using k-nearest neighbor classification to diagnose abnormal lung sounds. *Sensors*, *15*(6), 13132-13158.

Chen, J., Li, H., Tang, S., & Sun, J. (2002, June). A SOM-based probabilistic neural network for classification of ship noises. In *IEEE 2002 International Conference on Communications, Circuits and Systems and West Sino Expositions* (Vol. 2, pp. 1209-1212). IEEE.

Farcas, A., Thompson, P. M., & Merchant, N. D. (2016). Underwater noise modelling for environmental impact assessment. *Environmental Impact Assessment Review*, *57*, 114-122.

George, J., Cyril, A., Koshy, B. I., & Mary, L. (2013). Exploring sound signature for vehicle detection and classification using ANN. *International Journal on Soft Computing*, 4(2), 29.

Gupta, C. N., Palaniappan, R., Swaminathan, S., & Krishnan, S. M. (2007). Neural network classification of homomorphic segmented heart sounds. *Applied soft computing*, *7*(1), 286-297.

Hassaballah, M., Alshazly, H. A., & Ali, A. A. (2019). Ear recognition using local binary patterns: A comparative experimental study. *Expert Systems with Applications*, 118, 182-200.

Khan, S., Divakaran, A., & Sawhney, H. S. (2009, May). Weapon identification using hierarchical classification of acoustic signatures. In *Sensors, and Command, Control, Communications, and Intelligence (C3I) Technologies for Homeland Security and Homeland Defense VIII* (Vol. 7305, p. 730510). International Society for Optics and Photonics.

Král, P., Vrba, A., & Lenc, L. (2019). Enhanced local binary patterns for automatic face recognition. *In International conference on artificial intelligence and soft computing* (pp. 27-36). Springer, Cham.

Liang, H., & Nartimo, I. (1998, October). A feature extraction algorithm based on wavelet packet decomposition for heart sound signals. In *Proceedings of the IEEE-SP International Symposium on Time-Frequency and Time-Scale Analysis (Cat. No. 98TH8380)* (pp. 93-96). IEEE.

Mesaros, A., Heittola, T., & Virtanen, T. (2016, August). TUT database for acoustic scene classification and sound event detection. In *2016 24th European Signal Processing Conference (EUSIPCO)* (pp. 1128-1132). IEEE.

Romero, J., Luque, A., & Carrasco, A. (2017, February). Animal Sound Classification using Sequential Classifiers. In *BIOSIGNALS* (pp. 242-247).

Wang, C., Li, D., Li, Z., Wang, D., Dey, N., Biswas, A., ... & Shi, F. (2019). An efficient local binary pattern based plantar pressure optical sensor image classification using convolutional neural networks. *Optik*, 185, 543-557.

Wang, J. C., Wang, J. F., He, K. W., & Hsu, C. S. (2006, July). Environmental sound classification using hybrid SVM/KNN classifier and MPEG-7 audio low-level descriptor. In *The 2006 IEEE international joint conference on neural network proceedings* (pp. 1731-1735). IEEE.

Williams, R., Wright, A. J., Ashe, E., Blight, L. K., Bruintjes, R., Canessa, R., ... & Hammond, P. S. (2015). Impacts of anthropogenic noise on marine life: Publication patterns, new discoveries, and future directions in research and management. *Ocean & Coastal Management*, *115*, 17-24.

Xia, X., Togneri, R., Sohel, F., & Huang, D. (2017, July). Random forest classification based acoustic event detection. In *2017 IEEE International Conference on Multimedia and Expo (ICME)* (pp. 163-168). IEEE.

Xi-ying, H., Jin-fang, C., Guang-jin, H., & Nan, L. (2010, May). Application of BP neural network and higher order spectrum for ship-radiated noise classification. In *2010 2nd International Conference on Future Computer and Communication* (Vol. 1, pp. V1-712). IEEE.

Yang, S., Li, Z., & Wang, X. (2002). Ship recognition via its radiated sound: The fractal based approaches. *The Journal of the Acoustical Society of America*, *112*(1), 172-177.