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A new approach of hybrid decision tree based stair recognition

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***Abstract*— Blind people need some aid to interact with their environment with more security, especially, to avoid collision and falling. The process of staircase negotiation is complex for blinds. Therefore, an intelligent system is worth helping them. In this paper, we investigate incorporating only one ultrasonic sensor within an electronic white cane to detect and recognize floor and staircases. In our knowledge no previous work was concerned with such context. The performance of floor state recognition system depends on both signal processing strategy, extracting relevant information to represent objects, and classification approach, making the decision appropriate. In this paper, the proposed strategy consists on merging more than one transformation of ultrasonic signals used as feature in a hybrid decision tree. Such feature are extracted from various representations of ultrasonic signal allowing to see them from different viewpoints. Here our classification system is based on two levels. The first level is related to object detection. It is intended for triggering the second level, which is an concerned with stair case recognition. Our system is evaluated on a set of ultrasonic signals from a local database, where floor and staircases occur with different shapes. Using a multi-class SVM approach, accuracy rate of 88.1% is achieved.**

***Keywords*— Ultrasonic signal, Wavelet Transform, Frequency representation, Staircases detection.**

I. Introduction

Floor state recognition under different viewing conditions is a big challenge in electronic white cane. A successful recognition is intended to enhance visually impaired people security with low cost solutions.

Until now, only Yuan et Manduchi [1] have proposed a floor state recognition option in their proposed virtual white cane system. This system offers high detection rates of staircase but makes use of two sensors: camera and Laser (the Laser one being very expensive). We are concerned here of designing floor state detection white cane based on only one ultrasonic sensor, which is still a big challenge for such tool.

Exploiting efficiently the ultrasound signal relies on both signal modality and the way that is processed to extract the relevant information enclosed in it.

Various information can be extracted from signal magnitude, but does not necessarily provide the best representation of the signal [2]. Sometimes, frequency representation is more important, especially, when specific information are integrated in frequency components. Fourier Transform (FT) is often used for transforming the collected signal from time based signal to frequency-based one [3], [4]. Numerous previous works have proposed various sets of ultrasonic features extracted from time and frequency domains. They investigated the feasibility of using such parameters for ultrasonic signal classification. In [5], authors confirm that time-domain ultrasonic features include the main discriminate components of the signals. In their work, authors noticed that echo magnitude gives an inadequate information and then cannot be used alone. Then, they propose as features time-domain characterizing the rectified echo signal envelope, combined with outputs of various preprocessing such as rectification, low-pass filtering, mean-subtraction and under-sampling [6]. In [7], Dror et al. demonstrate that echo representation in frequency domain gives the best results. In [8] and [9], authors have combined time and frequency domain features. In [10], the wavelet transformation has been shown as a useful tool for the enhancement and the interpretation of ultrasonic signal in the context of non-destructive evaluation. At present, methods based on discrete wavelet transform (DWT) are mainly divided into two families in ultrasonic signal processing. The first one uses thresholding scheme in discrete wavelet transform [11]- [14], where coefficients larger than a predefined threshold are preserved, otherwise they are set to zero. Then the signal is reconstructed with the preserved coefficients. The second family processes only the first scales of wavelet transform [15]-[18]. In [15], [16], the approximation coefficients of the first scales are used to reconstruct the signal. Results demonstrated in the second family (DWT), are promising and deserve special consideration of such features in our system.

In this paper, we explore ultrasonic signal potentials in object detection and mainly floor state recognition. In this context, a new strategy based on mainly merging FT frequency signal representation and wavelet transform coefficients, enabling construction of a hybrid decision tree, for reducing complexity. The main advantage of the proposed approach is that is can be handled with only small sample numbers (SSN) (30 samples).

The proposed strategy is potentially based on two levels in order to simplify the classification task and to accelerate the decision making process. In the first level, wavelet transform offers immunity with respect to ultrasonic noise. Accordingly, only one scale is used to reconstruct a denoised version of the original signal, which will be used to extract various discriminating features. In case of the presence of an obstacle, the second level operates. It is based on various frequency representations such as periodogram, smoothed spectrogram, averaged spectrogram, spectrum, etc. These different representations allow to see the signal from different viewpoints, which enables to extract distinct, complementary and redundant information. In both classification levels, Support Vector Machine (SVM) is used for its ability to learn in sparse, high dimensional space with relatively few training samples.

The remainder of this paper is organized as follows: In section 2, we present the background of our issue, where we describe ultrasonic signal processing for feature extraction and classification based on SVM. Then, the proposed strategy is detailed in section 3. Section 4 gives a performance evaluation of the proposed approach. Finally, we conclude and give some perspectives in section 5.

II. BACKGROUND OF THE ISSUE

Here we present firstly, ultrasonic signal processing based on Fourier transform and wavelet transform. Then, we give secondly a brief review of feature extraction and SVM based classification.

A. *Ultrasonic signal processing*

The ultrasonic sensor is often fixed to white cane, which is unstable due to the tapping and sweeping motion. This leads to an induced noise affecting the data. Accordingly, enhancement of the ultrasound signal becomes mandatory. In such condition, a low pass filter is used.

1) Fourier transform:

In this paper, various transformations in frequency domain are applied to ultrasonic signal which purpose is to extract distinct, complementary and redundant information. Fig.1 shows the different considered transformations.

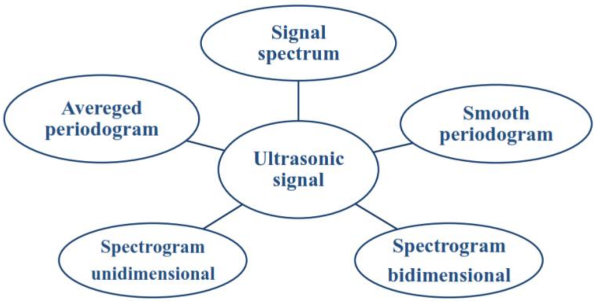

Fig. 1. Processed ultrasonic signal representations in frequency domain

- **Spectrogram representation** explains how the spectral density of signal varies with time. It can be estimated by computing the squared magnitude of the Short Time Fourier Transformation (STFT) of the signal. So that, the spectrogram is a time-frequency representation. This transform type decomposes the signal x over a family of time-frequency atoms $A_{t,f}$ where t and f are the time and the frequency localization indices, where x_i, $i=0,...N$, is an ultrasonic signals.
The resulting atom coefficients can be written as follows :

$$F[t,f]=\sum_{i=0}^{N-1} x[i]A^{*}_{t,f}[i] \qquad (1)$$

where * denotes the conjugate of A and the short-time Fourier atoms $A_{t,f}$ can be written as follows :

$$A[i]=w[i-tu]\exp\left(\frac{j2\pi ki}{K}\right) \qquad (2)$$

where w[i] is a Hanning window of support size K.

- **Spectrum representation** shows the magnitudes as a function of the frequency.
- **Periodogram representation** P estimates the signal spectral density. It can be estimated by using Fast Fourier Transformation (FFT) as shown in equation (3)

$$P=\frac{|fft(x)|^{2}}{N} \qquad (3)$$

- **Averaged periodogram** is used to improve performances obtained by the simple periodogram. It's estimation begins by cutting a plurality of adjacent signal frames. Then, a periodogram representation is done for each signal frame. Finally, an averaged periodogram on the different frames is computed.
- **Smoothed periodogram or Welch periodogram,** consists on calculating several periodograms based on a single signal, using a sliding window**.**

2) Wavelet transform:

The implementation of this transform consists on using a filter bank. In this paper, wavelet transform is used in conjunction with FT frequency representation, to improve system performances and reduce ultrasonic signal noise.

B. *Feature extraction*

Feature extraction is a procedure dedicated to underline relevant information in representing objects. In our proposed system, several features were extracted from each representation of the filtered ultrasonic signals xi, i=1, ...,N.

We define in the following, the extracted features from each time and frequency representation.

- **Time domain: filtered ultrasonic signal**

Feature 1: Mean

$$\bar{x} = \frac{1}{N}\sum_{i=1}^{N} x_i \tag{4}$$

Feature 2: Sample Standard Deviation is a measure that is used to know how signal spreads out:

$$s = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(x_i - \bar{x})^2} \tag{5}$$

Feature 3: maximum

$$mx = \max_{i=1,\dots,N}(x_i) \tag{6}$$

Feature 4: minimum

$$mn = \min_{i=1,\dots,N}(x_i) \tag{7}$$

Feature 5: Skewness is a measure of signal symetry:

$$\mu_3 = \frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})^3 \tag{8}$$

Feature 6: Kurtosis is a measure of whether the signal is flat.

$$\mu_4 = \frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})^4 \tag{9}$$

Feature 7: Root Mean Square (RMS) is a measure of the magnitude of a varying quantity:

$$V = \frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x}) \tag{10}$$

$$R = \sqrt{V} \tag{11}$$

Feature 8: The range between the maximum and the minimum of signal magnitude :

$$m = mx - mn \tag{12}$$

- **Frequency domain**

The spectrum : Features extracted from the spectrum are the same features computed from the filtered signal in time domain, illustrated in equations (5), ..., (12).

The spectrogram : This representation provides an image that is used to extract Haralik's texture features [23].

The periodogram : Features calculated from the filtered signal spectrum, are also extorted from the periodogram, in addition to other features that have been extracted from this representation which are:

feature 9: the variance performed according to equation (10).

feature 10: the bias

$$B = \frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x}) \tag{13}$$

C. Classification based on SVM

SVM is a supervised learning method that can be applied in classification. SVM classifiers are used in various real-world applications, and they are now established as one of the standard tools for machine learning and data mining [20]. SVM classifier advantageous is based on minimizing the principal bound taking into account classifier complexity and empirical error at the same time. In this way, SVMs are able to learn in sparse, high dimensional spaces with relatively few training samples [21]. They define an optimal separating hyper-plane which is used to classify an unlabeled input data, by applying the following decision function:

$$f(X) = sign[\sum_{x_i \in SV}^{n}(y_i \alpha_i K(x_i, X) + b)] \tag{11}$$

where SV is the set of support vector items x_i, α_i are the optimized Lagrange parameters, K is the kernel, b is the offset value, and y_i is the label of x_i, y_i may be either 1 or -1. The optimal separating hyper-plane is the one that maximizes the distance between itself and the nearest data point of each class. Different types of kernel can be used, RBF, Polynomial, etc... In our system, we use RBF kernel defined by :

$$K(x, x') = \exp\left(-\frac{1}{2}\frac{\|x - x'\|^2}{\sigma^2}\right) \tag{12}$$

with the parameter σ called the bandwidth, x and x' are two feature vector samples.

III. The Proposed Strategy

In general, object recognition system must be evaluated not only by their accuracy and reliability, but it is necessary to take into account processing time. Then, a good compromise between them is essential. Here, systems designed for visually impaired people must be real time to allow the user to react and to avoid collision.

It is certainly that by the use of several classes, represented by different information sources and their combination, the accuracy and reliability can benefit from information complementarity and diversity. However, the algorithmic complexity and the time processing will be as more important as the number of classes to discriminate is large. This has led us to investigate the level at which an alert should be transferred to the user. In the proposed application, blind persons, when moving in his environment, need to be alerted only when the cane detects an ascending or descending staircases. In that case, it will be not interesting to undergo a synthetic classification of the environment into three classes, even floor, ascending/descending staircase. Thus, we propose accordingly a new decision tree allowing to simplify the classification system. This has two classification steps in order to accelerate the process of decision making. The second step is operating only if the decision of the first indicates the existence of obstacle. In such condition, the second step is optional. Fig.2 illustrates this process:

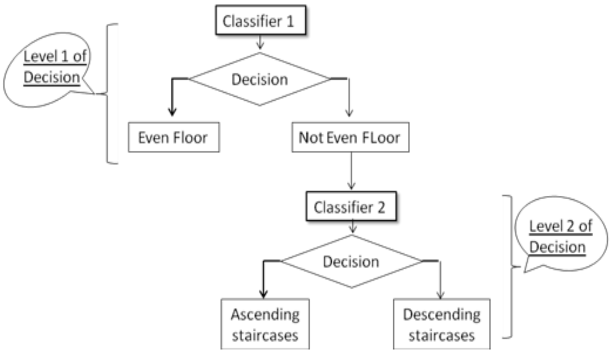

Fig. 2. Decision tree based on two classification levels for floor state identification

In this paper, we start by an investigations of a single wavelet based domain feature and then single FT frequency representation [22]. Then, for seek of more efficiency, we merge both wavelet and FT frequency representation. Accordingly, we are based on wavelet transform in the first level and Fourier transform in the second one. This choice is justified in the following section.

IV. EXPERIMENTS AND RESULTS

Two data set are created using research prototype [22], the first one is for parameter estimation and the second one is for generalization. Classification strategies in frequency and wavelet domains are presented in the following.

A. Classification in the frequency domain

The classification approach in the frequency domain is illustrated by Fig.3, where ultrasonic signal processing steps are based on extraction of different information sources.

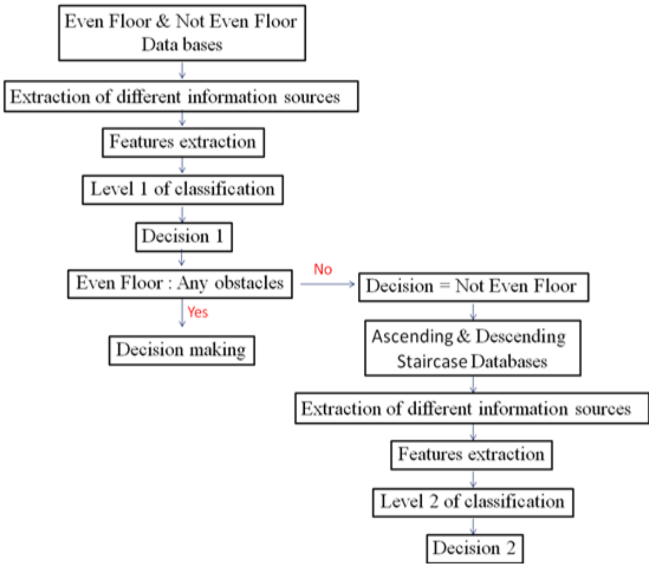

Fig. 3. Classification approach using two classification levels

Table 1 and Table 2 show classification performances for even/not even floor and respectively for ascending/descending staircases on our data set.

TABLE 1. CLASSIFICATION PERFORMANCES BASED ON FREQUENCY DOMAIN FEATURES OF LEVEL 1 OBTAINED BY OUR DATA SET

	Output classified as :	
Input known as:	**Even Floor**	**Not Even Floor**
Even Floor	82%	18%
Not Even Floor	13%	87%
Accuracy	85%	

TABLE 2. CLASSIFICATION PERFORMANCE BASED ON FREQUENCY DOMAIN FEATURES OF LEVEL 2 OBTAINED BY OUR DATA SET

	Output classified as :	
Input known as:	**Ascending staircases**	**Descending staircases**
Ascending staircases	94%	6%
Descending staircases	20%	80%
Accuracy	88,13%	

B. Classification in the wavelet domain

In the wavelet domain, we apply the same proposed classification approach illustrated in Fig.3, where ultrasonic signal processing steps are based on Haar wavelet transform.

Table 3 and Table 4 show classification performances for even floor/not even Floor and respectively for ascending/descending staircases on the our data set.

TABLE 3. CLASSIFICATION PERFORMANCE BASED ON WAVELET DOMAIN FEATURES OF LEVEL 1 OBTAINED BY OUR DATA SET

	Output classified as :	
Input known as:	**Even Floor**	**Not Even Floor**
Even Floor	78%	22%
Not Even Floor	1%	99%
Accuracy	91,95%	

TABLE 4. CLASSIFICATION PERFORMANCE BASED ON WAVELET DOMAIN FEATURES OF LEVEL 2 OBTAINED BY OUR DATA SET

	Output classified as :	
Input known as:	**Ascending staircases**	**Descending staircases**
Ascending staircases	97%	3%
Descending staircases	52%	48%
Accuracy	76,27%	

Table 3 shows on the one side that the wavelet domain improves classification performances for even floor and not even floor discrimination. On the other side, Table 4 demonstrates that the discrimination between ascending and descending staircases is better in the frequency domain.

These results demonstrate that a system performance rely mainly on the efficiency of the extracted features.

Analysis results, presented in Table 3, allow us to conclude that wavelet domain is able to eliminate signal noise and returns relevant information in the discrimination of not even floor.

In the next section, we will resort the complementary of both FT and wavelet based features. Then, a new approach is proposed consisting on combining frequency and wavelet domain.

C. Combination of frequency and wavelet domain

The proposed decision tree has to satisfy the following condition to be effective:

The first level must be efficient for stair case detection. In fact, it is this level that is triggered a user alert of risk existence. Using frequency domain in this level occurs 13% indicating Even Floor instead of Not Even Floor. This error rate, considered high, is improved to be only 1% using wavelet transformation. In this context, it is more advantageous to apply the wavelet transform in the first level. In the second level we make use of the frequency representation in order to benefit of its relevance. As can be seen, results show some average improvement from 85.05% to 91.95% in the first level, filling in the condition, declared previously.

V. Conclusion and future work

Signal processing is a fundamental step of recognition system. It is intended for reducing signal noise and extracting relevant information. In this paper, a new strategy is proposed to recognize three floor states, even surface, ascending/descending staircases, using ultrasonic signal. Our approach is based on wavelet transform to reduce signal noise and various frequency domain related representations offering different viewpoint of ultrasonic signal. The decision tree based on two classification levels. The advantages of our proposed strategy are justified by experimental results. Indeed, our method allows to simplify the classification system and accelerate the process of decision making. Results obtained from merging both performances have been compared to single wavelet based and FT based features showing better efficiency.

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