Acoustic Water Leak Detection System

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***Abstract*— This article presents an acoustic water leak detection system. It shows all the stages for doing acoustic leak signal processing and classification. The technique used for classification is support vector machine (SVM) using as features the Itakura mean and maximum distance and the larger projection of the principal component analysis (PCA). The whole process is based on the autoregressive (AR) models of the signals. Detection rate achieved is 80%.**

Keywords*— *Water Leak Detection; SVM; AR; PCA.

I. Introduction

Water leakage is a huge problem to the water utilities, due to the great amount of water wasted every day. According to Sabesp [3], the So Paulo water utility, the amount of water lost is around 26% of what is produced every day.

A leakage can be of three different kinds, namely: inherent, visible and not-visible. The inherent leakage is not visible and not detectable either, since it is a very small leak, like what happens in the first-stage corrosion's. The visible leakage is normally the one that grows throught the ground and can easily be found by the population. And the not-visible ones are those that cannot be seen, but can be found by the sounds it produces.

For the purpose of identifying not-visible leakage, some instruments are used. One of them is the geophone. The geophone is a device that captures the leakage sound with a special microphone. With this device, an expert can listen to this sound and identify if it is a leakage or not. Geophones may be mechanical or electronic in nature. The mechanical one only helps if the person who is listening to it is an expert in listening to leakage sounds. On the other hand, the electronic one has some filters and gain control that can help the expert to identify the sounds it captures, easily. We investigate techniques that help in automatic leakage detection, by means of the sounds produced by the leak in the pipe, acquired by a geophone.

A. About water Leaked sound

A leakage sound, as shown in Fig. 1, is produced by the collision of the water that goes through the pipes buried in the ground. Another source of sound is the vibration of the pipe induced by water pressure. Studies have shown that these sounds contain frequencies between 80 Hz to 5000 Hz. The intensity of the sensed signal is closely related with the depth, dimensions and material of the pipe [2]. The speed of sound in pipes made of metal is larger than in plastic pipes. Also, metal pipes produce sound frequencies higher than plastic ones.

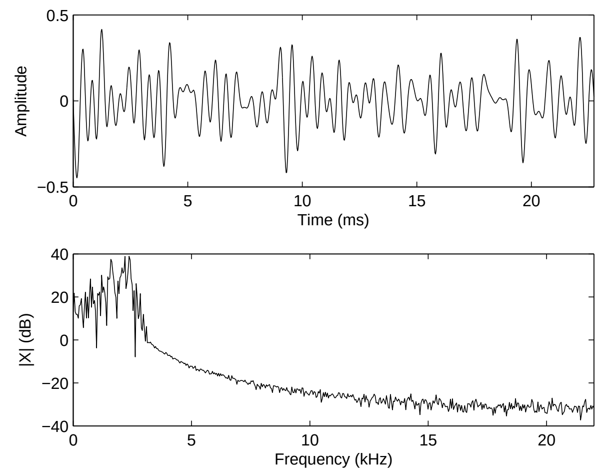

Fig. 1. A tipical leak signal frame sample and its spectrum

II. Leak sound feature extraction

In order to acoustically detect water leak, we should first extract from the original data some parameters that represent this information. In our work, we defined a group of three parameters as a feature vector. These three parameters are the mean and maximum Itakura distance between AR models and also the AR model projection on the first principal component of the reference AR models.

As a first step, each acoustic signal is segmented into a 20ms frame using a hamming window with and overlap of 50%. For each frame, its autoregressive (AR) model is calculated. Out of all signals used for training the system, an amount of 10 were selected to be parte of the reference models. This reference model is used to calculate the Itakura mean and maximum distance. Also these models are used to estimate the principal components of the AR model space. Those ten signals were selected randomly.

For a signal $x(n)$ with N samples, $n = \{1, 2, ..., N\}$, its AR model satisfies the Eq. (1), where the $\vec{a} = \{a_0, a_1, ..., a_{p-1}\}$ are the p AR coefficients. p is the AR model order and $\varepsilon(n)$ is its residual error signal.

$$x(n) = \sum_{k=0}^{p-1} a_k x(n-p) + \varepsilon(n) \tag{1}$$

A. Itakura Distance

Once all the AR coefficents of the signals are determined, the Itakura Distance is then calculated. This distance, first presented in [8], measures a mean of two distortions between the AR models of two signals. Using the AR model $\vec{a}$ defined before and defining $\vec{b} = \{1, b_1, b_2, ..., b_p\}$ as the AR model of signal $y(n)$. The Itakura distance between these two models is defined as follow:

$$d(\vec{a}, \vec{b}) = \frac{d_1(\vec{a}, \vec{b}) + d_1(\vec{b}, \vec{a})}{2} \tag{2}$$

where $d_1(.,.)$ is the Itakura distortion measure, as presented in Eq. (3). The $d_1(\vec{a}, \vec{b}) \neq d_1(\vec{b}, \vec{a})$ inequality holds since the distortion of $\vec{b}$ with respect to $\vec{a}$ is not equal to the distortion of $\vec{a}$ with respect to $\vec{b}$.

$$d_1(\vec{a}, \vec{b}) = \log \frac{\vec{b}^T R_a \vec{b}}{\vec{a}^T R_a \vec{a}} \tag{3}$$

In Eq. (3) the R_a is the autocorrelation matrix of model $\vec{a}$. In the same way, having R_b as the autocorrelation matrix of model $\vec{b}$, $d_1(\vec{b}, \vec{a})$ is written as:

$$d_1(\vec{b}, \vec{a}) = \log \frac{\vec{a}^T R_b \vec{a}}{\vec{b}^T R_b \vec{b}} \tag{4}$$

B. Principal Component Analysis

The Principal Component Analysis, PCA [7], is a method for determining a new vector base, for the original data, whose directions contain the most variability in the data information. These directions are known as the principal components. In our case, the base is constructed using l AR models of our reference data, each model contains p AR coeficients. The principal component vectors are calculated by extracting the eigenvectors of the covariance matrix of the reference data. Every new AR model will be projected onto this new space S, with dimension (pxl), as shown in Eq. 5.

$$\vec{a} = \vec{\lambda} S \tag{5}$$

In Eq. (5), $\vec{\lambda}$, with dimension $(1xl)$, is the vector projection of the input AR model $\vec{a}$ onto S. In our case, we define $l = 1$ since we use only the first principal component direction, which indicates the direction of most data variability.

III. Classification Technique

The water leak signal has not been studied at length for leak detection. In the references we have invetigated, three techniques have been used for this purpose, as follows: Neural Networks [5], Hidden Markov Model (HMM) [4] and Support Vector Machine (SVM) [9] [1]. As a first approach, SVM technique was chosen to be used in this work.

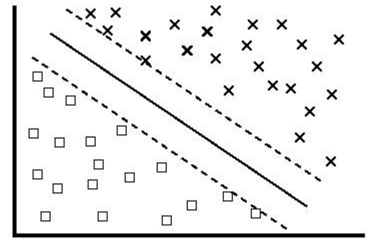

Fig. 2. Training data set points and the hyperplane showing how the data is separeted in two classes.

A. Support Vector Machine

Support Vector Machine [6] is a pattern classification technique that defines a p-dimensional Hyperplane, Eq. (6), which splits the training data set into two separable classes, as shown in Fig. 2. This p-dimensional hyperplane is constructed using some vectores from the trainning data set which are called support vectors.

In Linear SVM (LSVM), the hyperplane is defined by Eq. (6), where $\vec{w}$ is normal to the hyperplane, $\frac{b}{\|\vec{w}\|}$ is the distance from the hyperplane to the origin, with $b \in \Re$, and $\vec{a}$ is the imput data.

$$< \vec{w}, \vec{a} > + b = 0 \tag{6}$$

The inner product $< \vec{w}, \vec{a} >$ is defined by Eq. (7), where p is the hyperplane dimension.

$$< \vec{w}, \vec{a} > = \sum_{i=1}^{p} w_i a_i \tag{7}$$

In nonlinear SVM, the data is first mapped, with a nonlinear trasnformation, to a new higher dimensioned space, $\Phi(\vec{a})$, where there LSVM can be applied. In this case, the separable hyperplane is calculated by Eq. (8).

$$< \vec{w}, \Phi(\vec{a}) > + b = 0 \tag{8}$$

For classifying data vector $\vec{a}$, its projection onto the normal vector to the hyperplane must be calculated. If its projection is negative then it belongs to one side of the hyperplane, that is, to class one. On the other hand, if its projection is positive, then this point belongs to class two, as Eq. (9) sets out.

$$\text{class}(\vec{a}) = \begin{cases} 1 & \text{if} \quad \vec{w}.\vec{a} + b < 0 \\ 2 & \text{if} \quad \vec{w}.\vec{a} + b > 0 \end{cases} \tag{9}$$

IV. Experiment description and Results

The first step we took in the experiment was to define a database for training the classifier. For this purpose we had, until now, a set of 42 sounds sample, acquired with a geophone. Each one is 10 s long. We selected 10 sounds out of this set to be used as a reference base. We have made

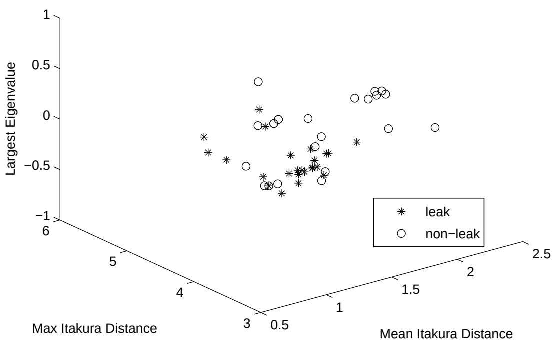

Fig. 3. Three-dimensional space with training data for classification by the SVM.

tests changing theses groups, randomly, and selecting the one which gives the best result.

With the reference base defined, the AR model coefficients were calculated, at each 20 ms frame of the signal. Each signal frame is obtained by applying a Hamming window with 10 ms overlapping. We used AR order $p = 10$. In Fig. 3 all training data shown is represented by the three features as defined before in Sec. II.

Using this three-dimensional representation, we then calculate the hyperplane that can better separate our data set into two groups. We have achieved a recognition rate of 80%, when testing with 21 sounds, where 11 signals contain leak sounds and the others are signals without leak.

V. Conclusion and Future works

We conclude from this research that automatic water leakage recognition can be done using the sound it produces by applying signal processing techniques. In our experimental tests, we get significant but not definitive results, mainly because of the training data set we have used, once the construction of our database is not completed yet.

As we can see in Fig. 3, some points are not located in the regions that would be easier for the SVM algorithm to define a good hyperplane. It is probably due to some noise contained in the signals, since they have not been filtered before processing.

We propose, for future works, to study the extraction of other parameters, for composing a new feature vector, in a way that we can have a better representation of the acoustic leak signal.

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