Intelligent Fence Intrusion Detection System: Detection of Intentional Fence Breaching and Recognition of Fence Climbing

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Abstract: This paper introduces a compact, cheap, and highly reliable fence breach detection system which can detect any activity on the fence and discriminate the type of activity. The hardware is based on utilization of a 3-axis accelerometer and a RISC microprocessor. The system is equipped with a wireless device which enables the system to work remotely and communicate with a base station. We have developed an algorithm to detect activity vs. no-activity on the fence. Moreover, the algorithm is capable of recognizing the type of the breach; whether the breach was due to rattling caused by strong wind or a person climbing on the fence. The recognition algorithm is computationally inexpensive therefore it can be embedded inside the local RISC microcontroller. The proposed system has been tested on different fences and demonstrated an over 90% correct recognition rate.

I. INTRODUCTION

Perimeter fencing is widely used to isolate and protect public and private places such as airports, military bases, power stations and construction zones against unauthorized accesses. Fence structures merely prevent a percentage of intrusions or postpone them. A higher level of security is needed to monitor and investigate activities on or around the fences. The Fence Intrusion Detection System (FIDS) is one of Perimeter Intrusion Detection Systems (PIDS) focusing on the fence intrusions. In general, there is no system practically available to classify suspicious activities; whether the activity was due to the strong wind turbulent or climbing of a person on the fence.

Existing FIDSs use a wide range of sensors to capture the fence activity. Gomery and Leach [1] used accelerometers to analyze fence vibration. Thiel [2] used cameras to monitor the activity, while Dibazar et al. [3] proposed geophone sensors to grab seismic signals created by intruders. Vries [4] analyzed the acoustic signal of the fence captured by microphones. Maki [5] introduced optical fiber sensors to monitor intrusion on the fences. Other types of sensors including capacitive, infra-red, magnetic or optical sensors have been suggested to capture activity around the fences.

So far, most of the research in fence security has focused on introducing different sensors for this application. Although there are many articles on sensor selection for this application, there are only few studies on intrusion classification. Moreover, the proposed methods are either case dependent -- and can not be easily generalized for different fences with different length, height, and sagginess -- or are expensive in terms of computational complexity and hardware platform. For example, Maki [5] has compared the signal level of sensor output with an adaptive threshold to detect the event on the fence. The threshold level of this system is continuously updated using background noises or environmental variations to keep the sensitivity of the system constant. This system is not capable of discriminating between horizontal vs. vertical movements (rattling vs. climbing). Vries has proposed an acoustic based system [4]. His system has employed a neural network classifier with frequency domain features which can detect intrusion (climbing, cutting and jumping) around fences. The system performance decays when the quality of the sound (or signal to noise ratio) generated by the intruders and surrounding environment decreases. Moreover, in order to locate the suspect, this system requires more than one sensor which makes the system complex and very expensive. Thiel's system is an image processing based system [2] which analyzes continuous frames of video to detect any suspicious activity around the fences. As with other optical systems, Thiel's system works under defined background conditions and fails if anything blocks the view of the camera. Dibazar et al. [3] have reported the use of a dynamic synapse neural network classifier to detect human or vehicles around the fences. This system mainly focuses on vehicle or human detection rather than fence motion.

In general, different activities on the fence can be categorized into five different classes including lean, rattle, kick, climb and no event [6]. Rattling and climbing are two main events of which the above mentioned events can be considered as a subset. Each of these two main events has different motion signatures. From a security point of view, the rattling is considered as the attempt of intrusion, while climbing could be a real intrusion.

In this research, we focus on making an Intelligent Fence Intrusion Detection System (IFIDS) to detect any suspicious activity on the fence and discriminate between climbing and rattling on chain-link fences. We introduce a compact, computationally inexpensive, and expandable FIDS which can be mounted easily on the fence.

This paper is organized as the following. In this application, a 3-axis accelerometer has been utilized as vibration sensing module. The output of the accelerometer is fed into a RISC microprocessor. We briefly explain the hardware in the section II. In section III of the paper, we talk about fence vibration properties during intrusion and quantifying them as features. In section IV, the classifier of this application is explained. We propose a Bayesian classifier and a state machine for dynamic classification. We also discuss the method of training of the classifier in section IV. In section V, we describe input event database, and performance of the system. Finally, in the last section, we cover the conclusion and possible improvements.

II. SENSOR MODULE

The IFIDS includes a 3-axis MEMS accelerometer, a RISC microprocessor and a Wireless module. It can be equipped with a power charging unit such as a solar cell. Figure 1 shows the Sensor block diagram plus its position on the fence.

The accelerometer measures fence vibration in three dimensions. The sensor can be installed anywhere in the fence panel, but the center of the fence is the optimum position for installation. Wave analysis in elastic planes shows that plane center receives maximum dynamic changes. Moreover, fences may or may not have a bar on the top. Likewise, the bottom of some fences is buried in the ground, while for some others it is free. In general, the center of different fences shows similar responses to the similar events occurring on the fence.

The accelerometer sensor measures static and dynamic acceleration along its three axes. The source of static acceleration is the earth gravity, while external force, causing vibration on the fence, creates dynamic acceleration. Based on the relative angle of the sensor axis to the direction of the earth's gravity, we can see the static acceleration in one or all three sensor axes. When an external dynamic force is imposed upon the fence, the relative angle of the sensor axes and the force direction makes the portion of acceleration to be projected into each axes. This is one the important properties that needed to be considered for developing a recognition algorithm.

The accelerometer measures -6 to 6 g force in each axis. The accelerometer output is sampled by one 10-bit ADC at 360 samples per second per channel.

In general, fences are parallel to earth's gravity direction. The IFIDS are installed on the fence in a way that the sensor X axis stays parallel to the earth gravity direction. In this circumstance, we have shown a few examples of sensor output in figure 2 in response to different events. Figure 2a shows sensor output when there is no motion on the fence. Figure 2b shows sensor output during rattling, while Figure 2c shows the sensor output during climbing. All figures include a five second frame of data. In the next section, we focus on the fence's dynamics and its features during different events.

III. FENCE MOTION FEATURES

The goal of this section is to explain features which have been employed throughout the paper. Recalling that the main two classes of events are rattling and climbing; this chapter discuses the features with which these two classes can be robustly represented. First, we

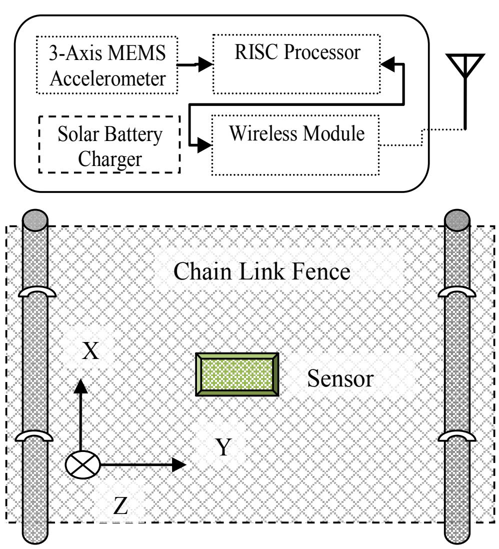

Fig. 2: IFIDS Sensor and Its Position on the Fence

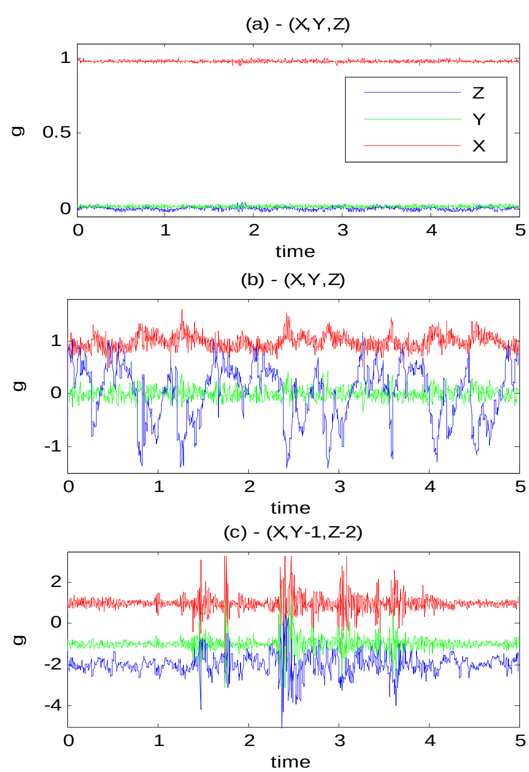

Fig. 1: 3-Axis accelerometer output in different motions of a fence (a) no-motion (b) rattling (c) climbing; time is in second

introduce a method which can discriminate activity vs. no activity. Then the activity class is further classified down into rattle and climb classes.

It is worth mentioning that since there is one to one correspondence between force and acceleration ($f=m.a$), classification of motion on the fence directly reflects the type of forces being imposed to the fence. In another words, in order to detect the type of force on the fence (or type of breach), the output signal of the accelerometer can be directly used.

As mentioned in the first paragraph of this section, the first intention is to find a feature with which presence of an activity on the fence vs. no-activity can be detected. In order to be able to suggest any statistical/mathematical approaches to this issue, it has been assumed that the output signal of the accelerometer is weakly stationary (mean and covariance stationary). This is a valid assumption if we consider the fact that the motion near the center of the fence has planar shift (rather than rotation).

Figure 2.a is an example which shows the sensor output when the fence has no or little vibration. There is no dynamic force on the fence, and the signal variance is very low. During rattling and climbing, there is always at least one dynamic force component causing fence acceleration (figures 2.b and 2.c) which makes the variance of the accelerometer signal to be higher than when there is no such activity on the fence. In the order to detect any event on the fence, the first feature can be *signal variation* S_v. S_v is defined as:

$$S_{v,k} = \sum_{i=k*N}^{(k+1)*N-1}(X_i - m_x)^2 + \sum_{i=k*N}^{(k+1)*N-1}(Y_i - m_y)^2 + \sum_{i=k*N}^{(k+1)*N-1}(Z_i - m_z)^2 \quad (1)$$

where K is the successive frame number. The histogram of S_v for data collected from different fences has been plotted in the figure 3. Based on this figure, S_v clearly is a good feature to discriminate activity vs. no-activity on the fence. The threshold for the classification can be estimated from the plot.

After detecting activity on the fence, the next step is to divide the activity class into two classes of rattling and climbing. Rattle can be defined as periodic fence movement mostly in Z axis. The periodicity is determined either by the force periodicity or fence natural resonance frequency.

Additionally, during a breach, the acceleration in X and Y axes are smaller than the Z axis. This property can also be observed in the rattling as shown in figure 2b.

The force pattern in climbing differs from rattling. When a person climbs on the fence, he/she exerts force upon different points on the fence with different intensities and direction which imposes non-periodic structure in the sensor output. In addition, there is significant level of acceleration in all three axes comparing to the one axis we had for rattling. Unlike

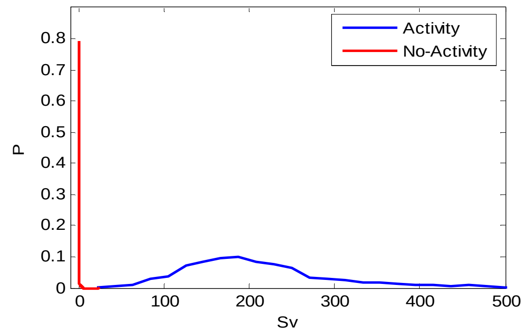

Fig. 3: Histogram of S_v for the activity and no-activity

rattling, there is no periodicity in Z axis when climbing happens.

Therefore, features which consider periodicity of the signal and relative energy of axes are selected for the classification.

To estimate natural damping frequency of the fence, an elastic plane was considered. For an elastic plane, the resonance frequencies can be calculated by ($n\pi/2l$), where l is the minimum of (height, width) of the plane and n is a positive integer. The fences are not elastic and because of their mass, they get at most the second resonant frequency if they resonate. For a typical 3×2 meter fence, its second resonant frequency will be less than 2 Hz. Therefore, we expect if wind or rain causes fences vibration, the resonant frequency will be less than 2 Hz. It also has been noted that intentional rattling made by human can not exceed 10 Hz (its second harmonic will be 20 Hz). Therefore, a filter bank with two filters was designed as depicted in figure 4. The first filter has a cutoff frequency at 20Hz and the second filter covers the rest of the frequency band. The energy of these two band-pass filters (*F1* and *F2*) are utilized as features.

In addition to the above-mentioned features, the relative energy of successive frames was also considered. In summary, the following features were extracted from the signals:

- Relative energy of X axis to Z axis ($E_{x/z}$)
- Relative energy of Y axis to Z axis ($E_{Y/z}$)
- Normalized energy of F1 in X axis ($E_{F1|x}$)

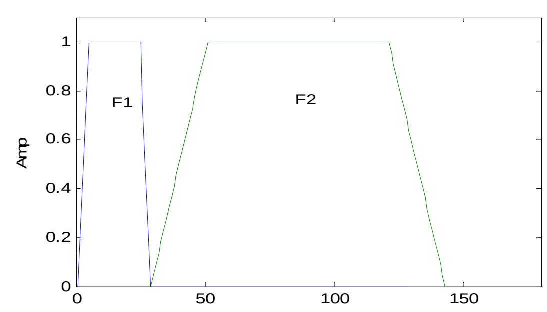

Fig. 4: Two filters employed for classification of rattling vs climbing

- Normalized energy of F2 in X axis ($E_{F2|x}$)
- Normalized energy of F1 in Y axis ($E_{F1|Y}$)
- Normalized energy of F2 in Y axis ($E_{F2|Y}$)
- Normalized energy of F1 in Z axis ($E_{F1|Z}$)
- Normalized energy of F2 in Z axis ($E_{F2|Z}$)

The sliding window length was 1.45 seconds with a 50% overlap (512 samples ~1.45 second). This was due to having at least one cycle of the signal inside the sliding window. Finally, for each frame of 1.45 second the feature vector was defined as following:

$$F = (S_v, E_{X/Z}, E_{Y/Z}, E_{F1|X}, E_{F2|X}, E_{F1|Y}, E_{F2|Y}, E_{F1|Z}, E_{F2|Z}) \quad (2)$$

The classifiers were formed based on feature vectors of equation (2) which is explained in the next section.

IV. CLASSIFIER

As mentioned earlier, after detecting any activity on the fence, the next goal is to classify the type of activity. The main two class of interest are rattling and climbing. Classifiers are formed based on features extracted from the output of the accelerometer (equation 2). The block diagram of the classifier is shown in figure 5.

The activity classifier compares the S_v with an adaptive threshold and decides whether the fence is in an activity or non-activity state. The threshold value in this classifier is adapted by checking variation of energy of the sensor output (S_v) in previous no activity frames. Using this technique, the classifier sensitivity to the wind or rain can be adjusted by information from previous frames. Equation (3) provides a recursive adaptation algorithm which is computationally inexpensive for calculating variation of the signal.

$$\begin{aligned} &M_{new} = \alpha * M_{old} + (1-\alpha) * S_v \\ &S_{new} = \gamma * S_{old} + (1-\gamma) * S_v^{\,2} \\ &Threshold = M_{new} + k * S_{new} \quad \text{if the frame is no-activity} \end{aligned} \qquad (3)$$

where M is the mean of S_v, S is the standard deviation of S_v, and (α, γ, k) are a constants. α and γ were set to 0.1 and k was 2 in our application. For initializing M and S, mean and variance of the first frame was used.

After detecting activity on the fence, features of the signals are extracted. Since distribution of features look like a Gaussian distribution (figure 6), Gaussian Mixture Models (GMM) were set up to model the feature space. Only one Gaussian mixture was employed in this application. The training of GMMs was performed using the EM algorithm. In order to enhance performance of the recognition, one GMM was also formed to model the no-activity state. This helps to reject false detection of activity on the fence.

Along with the GMM models for three classes of rattling, climbing, and no-activity; a state machine was also utilized. The three-state machine makes final decision making based on the most likely transitions of the last events and the current event. The classifier checks three (or five) consecutive frames and counts occurrence of different events. The events with more occurrences will be determined as the most likely class. Figure 7 shows the event classifier block diagram.

The next step is to define the state transition probabilities between classes. We defined the following 3 by 3 matrix for the transition parameters. This was only based on observations; however the EM algorithm can be used to deduce the state transition matrix more accurately.

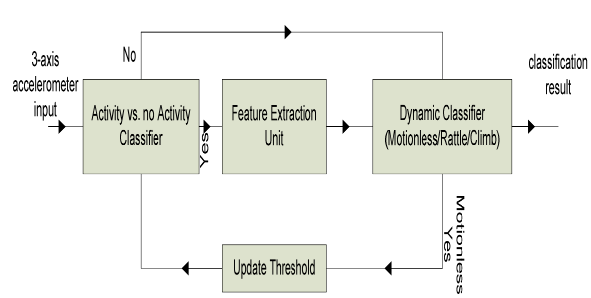

Fig. 5: IFIDS Classifier

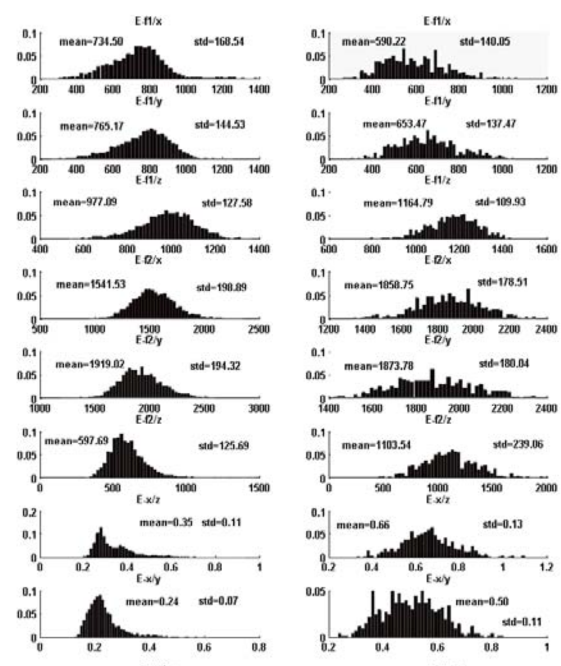

Fig. 6: Histogram of the Features in Rattling and Climbing

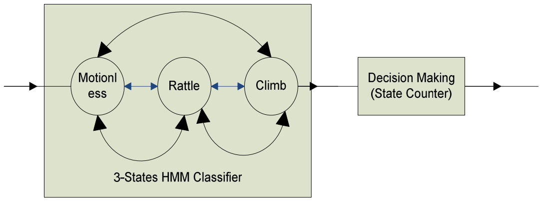

Fig. 7: Event Classifier

$$S=\begin{bmatrix} S_{na\rightarrow na} & S_{na\rightarrow rt} & S_{na\rightarrow cl} \\ S_{rt\rightarrow na} & S_{rt\rightarrow rt} & S_{rt\rightarrow cl} \\ S_{cl\rightarrow na} & S_{cl\rightarrow rt} & S_{cl\rightarrow cl} \end{bmatrix}=\begin{bmatrix} 0.33 & 0.33 & 0.33 \\ 0.3 & 0.4 & 0.3 \\ 0.3 & 0.3 & 0.4 \end{bmatrix} \quad (4)$$

where *na*, *rt*, and *cl* are no-activity, rattle, and climb respectively.

V. RESULTS

The sensor was installed on three different fences. One of the fences was loose, while two other were tight. The size of loose fence was 2.5 x 2.2 meters (width*height). Two other fences had 3 x 2.2 and 4 x 2.5 sizes. On each fence, two persons were asked to climb or rattle the fence and 72 data clips were recorded (see Table I for more details).

Table I: Database information

Event Type	No. of events	Duration of event (seconds)	Test Condition
Activity	2	420	▪ Motionless or windy condition
Rattling	50	30	▪ 2 different persons ▪ Different position on the fence ▪ Different speed
Climbing	20	15	▪ 2 different persons ▪ 3 time attempts

The whole data was divided into two parts: training and testing. The classifiers were trained using train data set and tested with test data. Figure 8 shows an example of classification result for two samples of data. In this example, the classifier has successfully discriminated rattling and climbing from background (no-activity). The classification results for test data is listed in table II. Table II is also the confusion matrix for these classes.

Table II: Classification result (confusion matrix)

Detection Rate (%)	Motionless	Rattling	Climbing
Motionless	100	0	0
Rattling	0	90.4	9.6
Climbing	0	1.8	98.2

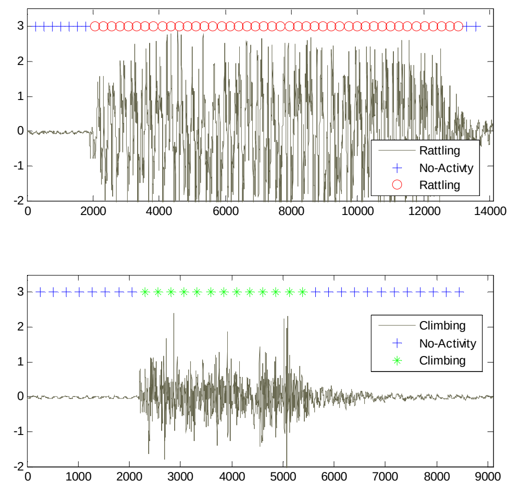

Fig. 8: Classifier Output in Two Different Data Frames

Table II shows that the system has more than 95 percent accuracy in the classification of events. The system's maximum false rejection rate is 5 percent and maximum false acceptance rate is 6 percent. A review of the misclassified data shows that most of the errors occur in the transition between no-activity and event frames. Another common type of error is rattling which happens between climbing events. Indeed, a climber pauses few times before he/she finishes his/her climb. During each pause, the fence rattles in its natural damping frequency (or no-activity). Figure 9 shows one of these cases.

To check IFIDS performance, we installed the sensor on a fence in a location in Joshua Tree, CA for more than 2 days and then we monitored the fence with a camera. The false acceptance rate for no-activity was zero during these periods. The real time test result confirmed the IFIDS' stability and performance.

VI. CONCLUSION AND FUTURE WORK

In this paper, we presented a cheap and compact

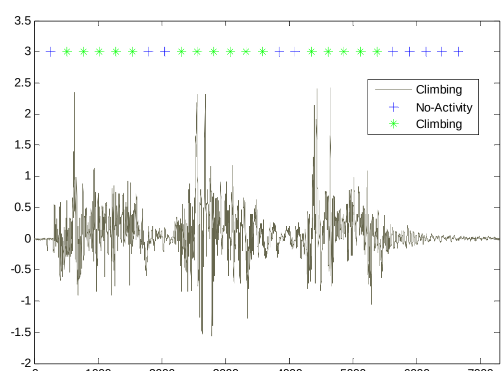

Fig. 9: Detecting Rattling Event Between Climbing Event

system which detects suspicious activities on the fence and discriminates between rattling and climbing. The system can be employed in windy or rainy conditions without any alteration in the algorithm. The system performance was above 90% for the data recorded from three different fences – off-line test – and a two-day – real time test – test in the Joshua Tree, CA.

It has been planned to install the system on fences of different sizes and shapes both to check the long term performance of the system and to record more data. The long term recording of the data will be used to update the model and enhance performance.

In all experiments reported in this study, the sensor was installed in the center of the fence such that the z-axis of accelerometer was perpendicular to the fence and x-axis along the earth gravity direction. We will test the performance of the system when the sensor is installed off of the center of the fence at different relative angles with respect to the earth gravity direction. The algorithm might need modification if the sensor is installed at a different location on the fence.

Rattling or climbing of a fence generates harmonics which propagate to the adjacent panels. The propagated harmonics of the adjacent panels may cause false positive recognition. This is something which we want to test in near future.

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