Optimal estimation techniques to reduce false alarms in railway obstacle detection

Juan J. García, Cristina Losada, Felipe Espinosa, Jesús Ureña, Álvaro Hernández, Manuel Mazo, Carlos de Marziani, J. A. Jiménez, Ana Jiménez

Department of Electronics. University of Alcalá
Alcalá de Henares. Madrid. SPAIN
jesus@depeca.uah.es

Fernando Álvarez

Department of Electronics and Electromechanical Engineering. University of Extremadura. Cáceres. SPAIN

Abstract **– This work presents some methods to reduce false alarms in railway obstacle detection. The sensorial system is based on one barrier of infrared emitters and another of receivers, placed on opposing sides of the railway. Obstacle detection is achieved by the lack of reception in the detectors. On the one hand, the efficiency of the system is achieved with the geometrical distribution of the sensorial system and the codification used in the emitting and receiving stages. On the other hand, optimal estimation techniques have been proposed to avoid false alarms, based on Kalman and H_∞ filtering. Principal Component Analysis is developed to validate the obstacle detection, and to improve the accuracy of the system. A high reliability under adverse conditions is obtained with the barrier, it being possible to detect the presence of obstacles, and to report on their position.**

I. INTRODUCTION

In today's railway systems, it is becoming more and more necessary to make use of safety features in order to avoid accidents.

In this work, one of the causes that can provoke serious accidents is analysed: the presence of obstacles, either stationary or moving, on the track. On railways, there are areas where an obstacle is more likely to appear, such as in the case of bridges or railway crossings. On high-speed lines, zones close to bridges are considered to be quite critical, since obstacles can easily fall onto the track. This can be caused by landslides, or simply by the fall of a vehicle or the transported material onto the line. The problem of landslides can also happen at the entrances and exits of tunnels. In these critical areas, systems are usually placed to detect the presence of obstacles [1][2], so that reports can be made to the control system. In this way, railway traffic can be halted and possible accidents avoided.

However such detection systems also present the problem of generating false alarms, thus creating financial losses whenever the system detects an obstacle which does not, in reality, exist.

Regarding this problem, this work is complementary to [3], where the authors presented the sensorial system, emission codification and obstacle location. In this study we review those aspects briefly, to analyse false alarms discrimination in depth. Optimal estimation techniques based on Kalman filter and H_∞ filtering are tested to reduce false alarms. Finally, we propose the use of *Principal Component Analysis* to validate the obstacle detection in the supervised area.

II. SENSORIAL SYSTEM AND GEOMETRICAL DISTRIBUTION

For the application described in the previous section, the trend is the use of optical sensors, either infrared or laser [1]. Irrespective of the sensor type chosen, all the details, that will be discussed bellow, can be applied to both types. The choice of the system may depend on financial considerations. In our study, the results shown bellow have been obtained using infrared emitters.

Infrared barriers usually consist of emitter-receiver pairs, each placed on opposing sides of the line, so it is only possible to detect the presence of an obstacle, but not its exact position. In order to detect obstacles on the railway, and distinguish at least vital areas (on the track) from the non-vital areas (to the side of the track), a special structure has been designed. In this case, every emitter provides three beams (multi-emission): one impacts on the receiver placed at the axial axis, and the other two on the receivers at either side, as is shown in Figure 1.

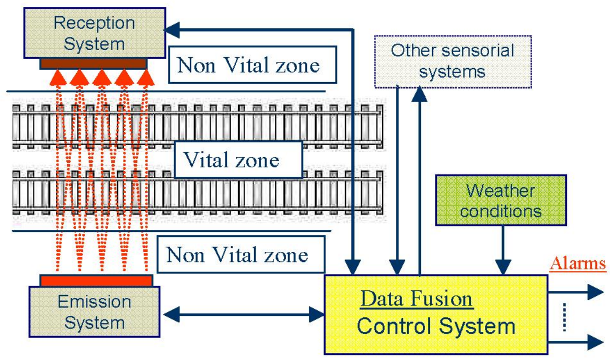

Fig. 1. Infrared barrier, placed in a railway sector.

The distance between emitting sensors is 25 cm, in order to detect 0.5x0.5x0.5m objects successfully (the size determined by railway regulations). The configured distance between emitters and receivers is 14 meters on a high-speed line. Basically, the method of obstacle detection, and its location on the railway, is based on the lack of reception on detectors. For a more detailed discussion, see [4].

III. EMISSION CODIFICATION

The emission is carried out in a continuous way by the emitters; and when the receivers do not detect this emission, the presence of an obstacle can be concluded. According to the geometry of the system in Figure 1, the radiation coming from three emitters is received by every receiver. In order to be able to discriminate the source of these emissions, it is necessary to code every emission. If interferences among the three codes are not desirable, mutually orthogonal (MO) sets of sequences have to be used. For a more detailed discussion about MO sets of sequences, see [5][6].

A. Codification

A complementary set of sequences is a set of binary sequences whose elements are either +1 or – 1, having the property that the sum of their aperiodic auto-correlation functions equals zero for all nonzero time-shifts. In particular, if *{a,b,c,d}* is a set of four sequences [7] with length *L,* and ϕ_{xx} represents the auto-correlation function of the sequence *x[k]* then:

$$\begin{aligned} &\phi_{aa}(k)+\phi_{bb}(k)+\phi_{cc}(k)+\phi_{dd}(k)=4L, \text{if } k=0 \\ &\phi_{aa}(k)+\phi_{bb}(k)+\phi_{cc}(k)+\phi_{dd}(k)=0, \text{otherwise} \end{aligned} \qquad (1)$$

Given two sets $\{a_1,b_1,c_1,d_1\}$ and $\{a_2,b_2,c_2,d_2\}$, they both are orthogonal if addition of cross-correlation function of the sequences of each set is zero. If ϕ_{xy} represents the cross-correlation function of the sequences *x[k]* and *y[k]* then:

$$\phi_{a_1a_2}(k)+\phi_{b_1b_2}(k)+\phi_{c_1c_2}(k)+\phi_{d_1d_2}(k)=0 \quad \forall k \qquad (2)$$

The set used in the emitter, not only discriminates the source of the emission, but also provides a high noise immunity to the system, as the obtained results show.

Figure 2 shows the mentioned situation, but with four emitters and one receiver. The emitter and receiver units are synchronized, mainly because of safety reasons in the described application.

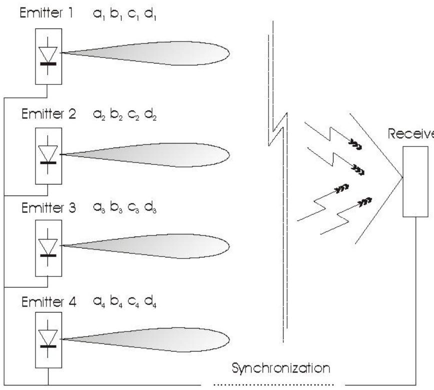

Fig. 2. Detail of the four emitters and the receiver.

In Figure 2, every emitter *i* transmits the set $\{a_i, b_i, c_i, d_i\}$ continuously. Its continuous emission allows a signal to be obtained in the detector with period *L* with a maximum peak of *4•L*, showing that there is not an obstacle between the emitter and the receiver, according to (1). The index *i* means any emission in the system, $i=\{1, 2, 3, 4\}$.

$$Detector\_output_i = z_i[k] = 4L\sum_{j=-\infty}^{j=\infty}\delta(k-j\cdot L) \qquad (3)$$

Figure 3 shows the results when using 256-bit sequences, with a SNR of -6 dB. The continuous emission provokes a periodical detector output, according to (3).

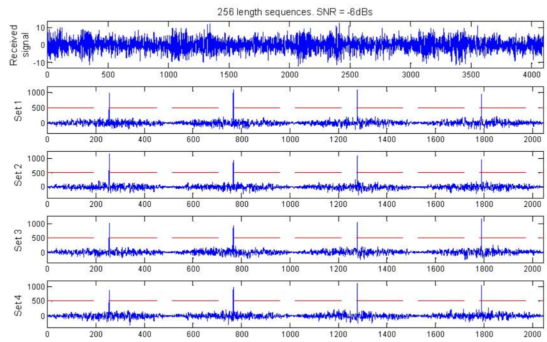

Fig. 3. Detector output for every emission. (L=256, SNR=-6dB).

The period depends on the sequence length. In this system, using 256-bit sequences, a peak is obtained in the detectors every 5.12 ms without any obstacle. The peak detector threshold is fixed to 2•L=512. The correlation system (see Figure 5) has been implemented in a FPGA, and Figure 4 shows the real detection without obstacles. If an obstacle is detected in front of a receiver, the peaks shown in Figure 5 disappear, being the output null while the obstacle is in the railway.

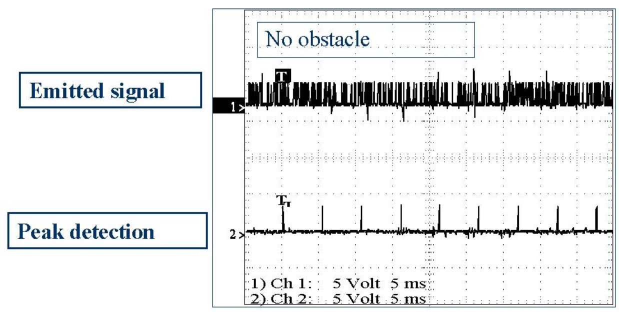

Fig. 4. Real detection every 5.12 ms without obstacles.

IV. FALSE ALARMS DISCRIMINATION

The outdoor infrared system suffers from diverse losses and disturbances, which can produce a wrong detection. If the receiver does not detect one emission during a predefined time, an alarm will be generated, informing that there is an obstacle. But if the obstacle does not exist, the alarm is actually false. As far as possible, it is necessary to avoid the false alarms generation, so, they have to be discriminated. We propose the use of optimal estimation techniques to reduce false alarms.

A. False alarms generation

In these outdoor optical systems there are some phenomena that can provide false alarms, mainly the weather condition and the solar radiation. There are other reasons, as propagation losses or wrong alignment among emitters and receivers. We assume that the last ones have been already considered in the link design.

1. Atmospheric attenuation. Snow, fog and rain are considered. Although there are numerous studies about the losses due to the meteorology, the expression (4) is used to quantify them [8].

$$L_{atm}(dB) = \frac{13}{V} \cdot R \qquad (4)$$

where V is the visibility in kilometres and R is the link range in kilometres. Table I shows the relation between weather condition and the visibility.

TABLE I
RELATION BETWEEN VISIBILITY AND WEATHER CONDITION

Visibility V	**Weather condition**
V>50km	Very clear
6km<V<50km	Clear
1km<V<6km	Haze /snow /light rain
0.5km<V<1km	Light fog /snow / heavy rain
V<0.5km	Thick fog

If this attenuation is very strong, the correlation level can not be high enough, and the system can consider that an obstacle exists.

2. Solar interference. As the photodiode wavelength (850nm) is inside the solar spectrum, natural background light can potentially interfere with signal reception. The solar effect in the IR barrier is the photodiode saturation [9]. It implies that the sequence detection does not work, providing a lack of reception as if there was an obstacle.

B. False alarms discrimination using the Kalman filter

When there are neither obstacles on the railway nor false alarms, the correlator outputs are shown in Figure 5.

In this situation, when there is a lack of signal due to weather conditions or solar interference, false alarms can be produced. To avoid this, in [3] the use of a dynamic threshold for the peak detector was proposed, where every correlator output was estimated by polynomial interpolation of degree 1, and the estimated output was used to change the threshold periodically. But as was shown in [3], whilst the false alarms were reduced, they were not completely eliminated.

To improve the system, we propose the Kalman filter (KF) to estimate the system output, and to obtain the dynamic threshold. Due to the fact that the system output changes according to the weather conditions, equation (3) will be

$$z_k = 4 \cdot L \cdot \theta_k + \phi_{\eta_k} \qquad (5)$$

where θ_k represents the atmospheric attenuation, ϕ_{η_k} is the component noise (correlation between the sequences and the noise), and k is the time instant when the correlator output is obtained. Taking into account (4), in a 14 meters link (the distance among emitters and receivers in the obstacle detection system), atmospheric attenuation is

$$\theta_k = 10^{-\frac{18.5}{V_k}} \qquad (6)$$

Where V_k is the value of the visibility in the instant k.

Now, we consider a discrete-time system represented by the state and output equations

$$\begin{aligned} \mathbf{x}_{k+1} &= \mathbf{\Phi x}_k + \mathbf{\Delta u}_k + \mathbf{\Gamma w}_k \\ \mathbf{z}_{k+1} &= \mathbf{C x}_{k+1} + \mathbf{v}_k \end{aligned} \qquad (7)$$

where, $\boldsymbol{x}$ is the state vector, and in this case $\boldsymbol{x}=\theta$ (the atmospheric attenuation), and $\boldsymbol{u}$ is the visibility variation. Here, $\boldsymbol{w}$ is the *process noise* (system disturbances, modelling errors, etc) with covariance matrix $\boldsymbol{Q}$; $\boldsymbol{z}$ is the measurement vector and $\boldsymbol{v}$ is the *measurement noise*, with covariance matrix $\boldsymbol{R}$, all of appropriate dimensions. To apply the KF, it is assumed that the noise signals be of zero mean value, that is, E[$\boldsymbol{w}$]=E[$\boldsymbol{v}$]=0. The best estimate that (7) can give is therefore:

$$\hat{\mathbf{x}}_{k+1|k} = \mathbf{\Phi x}_{k|k} + \mathbf{\Delta u}_k \qquad (8)$$

the *predicted measurement* is

$$\hat{\mathbf{z}}_{k+1} = \mathbf{C}\hat{\mathbf{x}}_{k+1|k} \qquad (9)$$

the *prediction error* is defined as

$$\tilde{\mathbf{z}}_{k+1} = \mathbf{z}_{k+1} - \hat{\mathbf{z}}_{k+1} \qquad (10)$$

and a recursive estimator can be represented as

$$\hat{\mathbf{x}}_{k+1|k+1} = [\mathbf{I} - \mathbf{KC}][\mathbf{\Phi}\hat{\mathbf{x}}_{k|k} + \mathbf{\Delta u}_k] + \mathbf{Kz}_{k+1} \qquad (11)$$

The choice of the gain matrix $\boldsymbol{K}$ determines the filter's performance. The *estimation error* is defined as:

$$\tilde{\mathbf{x}}_{k+1} = \mathbf{x}_{k+1} - \hat{\mathbf{x}}_{k+1|k+1} \qquad (12)$$

And the covariance matrix of the estimation error is defined as:

$$\mathbf{P}_k = E[\tilde{\mathbf{x}}_k \tilde{\mathbf{x}}_k^T] \qquad (14)$$

The design of the KF follows from a decision to choose the gain matrix $\boldsymbol{K}$, so that the covariance matrix $\boldsymbol{P_k}$ is minimized. The KF for the minimum-variance estimate is given by a recursive scheme, that can be analyzed in [10].

In this particular case, to apply KF, equation (6) has been linearized for a visibility of 1 kilometre. The following values have been considered:

$$x_k = \theta_k$$
$$u_k = V_k - V_{k-1}$$
$$\Phi = 1; C = 4L; \Delta = \left.\frac{\partial\theta}{\partial V}\right|_{V=1km}; \Gamma = 1$$

Using the KF, the system output is estimated, and according to such output, the threshold is determined to be half of the estimation. Figure 5 shows the block diagram of the system for 4 emitters and one receiver, with the periodical threshold correction. The reception block is the same for every receiver, but the codification set has been changed.

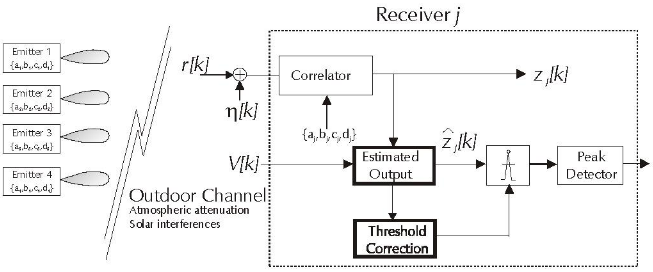

Fig. 5. Block diagram of the system with dynamic threshold.

The algorithm has been simulated in different weather conditions with a SNR=-6dB. In Figure 6, the first graph shows the correlator output for different weather conditions, the estimated output and the dynamic threshold. The central graph shows the peak detector output, but using the dynamic threshold with the polynomial interpolation of degree 1 [3]. The graph at the bottom shows the peak detector output using the dynamic threshold obtained with the Kalman filter, and in this case, all the obstacle detections are correct. We can conclude that in these conditions, the Kalman filter reduces the false alarms due to atmospheric attenuation.

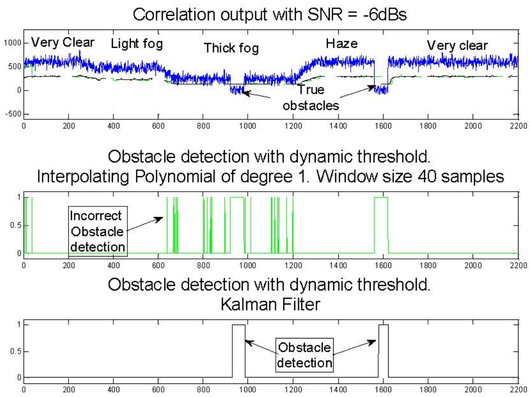

Fig. 6. Dynamic threshold evaluation in different weather conditions, using a polynomial interpolation and the Kalman filter.

Figure 7 shows the simulation with different relative levels of sunlight, increasing with time, and with a SNR=-6dB. The higher the solar radiation is, the lower the correlator output is. In such a situation, the dynamic threshold works better with the Kalman filter than the polynomial interpolation.

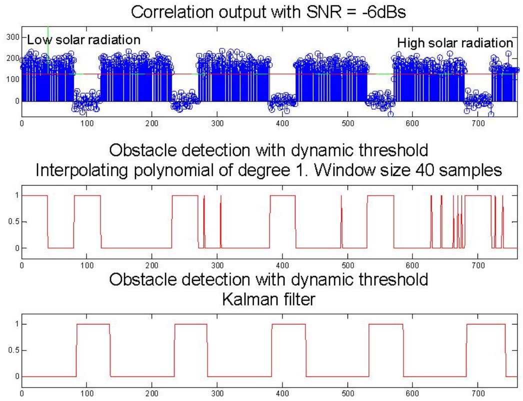

Fig. 7. Dynamic threshold evaluation with different relative levels of sunlight.

The KF works without any problem in the situations illustrated above, but there are a couple of serious limitations: it assumes that the statistical noise of the channel is known and it minimizes the average estimation error. Figure 8 shows a situation where the noise is not zero mean, and its covariance matrix is unknown. As can be seen, obstacle detection does not always occur. In order to solve this, we propose the use of other filtering techniques in the next section.

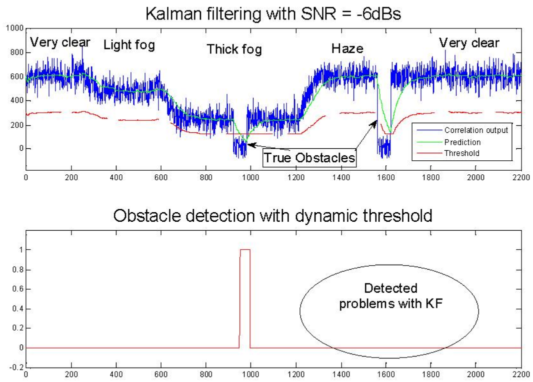

Fig. 11. Wrong obstacle detection using Kalman filter.

C. False alarms discrimination using H_∞ filtering

In this work the H_∞ filtering, also known as *minimax* filtering [11][12], is proposed for two basic reasons: this system is based on infrared technology and it is difficult to characterize the channel noise; furthermore, due to the relationship between the transport safety and the correct operation of the obstacle detector, it is important to minimize the worse case (and not only the average) of the estimation error.

With the receiver information and with a detailed knowledge of the dynamic of the system, the ***x*** estimation (by applying H_∞ criteria [13]), is carried out minimizing the index

$$\mathbf{J} = \frac{ave\|\mathbf{x}_k - \hat{\mathbf{x}}_k\|_{\mathbf{Q}}}{ave\|\mathbf{w}_k\|_{\mathbf{W}} - ave\|\mathbf{v}_k\|_{\mathbf{V}}} \qquad (15)$$

even in the worse case of *process noise* $\boldsymbol{w}$ and *measurement noise* $\boldsymbol{v}$, for which the average values (*ave*) are taken over all time samples *k*. On the other hand, $\mathbf{Q}$, W and V are diagonal matrixes that are used in the weighted norms in J and must be chosen by the designer. To make the estimation problem easier, the relation is assumed to be

$$\mathbf{J} < 1/\gamma \qquad (16)$$

where γ is some constant number chosen by the designer. In other words, the aim is to find a state estimate so that the maximum value of J is always less than $\boldsymbol{x}$, regardless of the terms $\boldsymbol{w}$ and $\boldsymbol{v}$. Furthermore, γ has to be chosen so that all the eigenvalues of the $\mathbf{P_k}$ matrix have magnitudes less than one. In [13] there is a more detailed discussion about H_∞ filtering, and as can be seen a recursive scheme is used to obtain the state estimation.

Figure 12 shows the results by applying *minimax* filtering to change the threshold periodically, in different weather conditions, and with a SNR=-6dB, as is shown in Figure 11, where there was a wrong obstacle detection with the KF.

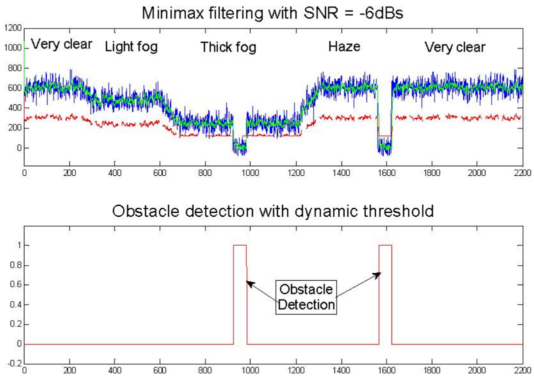

Fig. 12. Dynamic threshold evaluation in different weather conditions, using *minimax* filtering.

V. VALIDATION OF OBSTACLE DETECTION

In a railway environment, typical situations that can generate a false alarm must be identified. Although, the occurrence of false alarms has been notably reduced through of the use of the optimal filtering, it is still possible for some receivers not to detect the emission because a small object has temporarily interrupted the beam. Typical sporadic cases of cuts of the beams can be either leaves or small animals in movement. To filter these situations, it is proposed to use a posteriori signal processing based on *Principal Component Analysis* (PCA) [14], so that the above mentioned situations do not cause alarm activations.

In general, PCA is divided into two phases. The first one is carried out *off-line*, when varying operational conditions have been taken into account (conditions of lighting, meteorology, noise levels, etc), with the section of track free of obstacles, in order that a transformation matrix $\mathbf{U}$ between the original space and the transformed space, or vice versa, be obtained. The $\mathbf{U}$ matrix is obtained from the eigenvectors associated with the most significant eigenvalues of the covariance matrix of the data set. The second phase is *on-line*. By using the transformation matrix, the measurements that are received from the process unit (vector of measurements taken from the receivers) are projected in the transformed space according to:

$$\mathbf{y} = \mathbf{U}^T\mathbf{x} \qquad (17)$$

Later the reconstruction is computed

$$\hat{\mathbf{x}} = \mathbf{U}\mathbf{y} \qquad (18)$$

Where $\boldsymbol{x}$ is the *n-dimensional* vector of characteristics with zero mean, on which the transformation is carried out; $\boldsymbol{y}$ is the resultant vector from the transformation and represents the reconstruction vector. The reconstructed information will differ from the original in either major or minor magnitude depending on the grade of similarity that exists between the new data and those which were used to obtain the transformation matrix. This difference is known as the reconstruction error:

$$\varepsilon^2 = \|\mathbf{x} - \hat{\mathbf{x}}\| \qquad (19)$$

If the error is bigger than an imposed threshold, it concludes that an object exists.

Because the different receivers are very close, a high correlation generally exists among different components of the vectors, so that PCA notably reduces any redundant information. In order to consider all the possible scenarios of detection in absence of obstacles, the information of the off-line process has been obtained for different values of the SNR (from -6dB up to 6dB), as well as in different conditions of visibility, showed in Table I.

Figure 13 shows the reconstruction error when a pedestrian is crossing the tracks transversely. In every time instant a group of receivers detect the presence of the above mentioned obstacle.

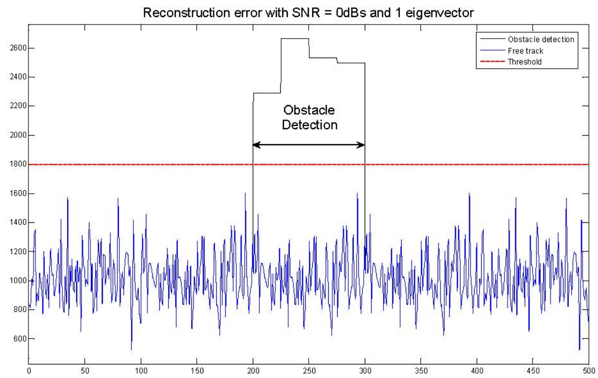

Fig. 13. Reconstruction error when the section of track is not free.

As Figure 13 shows, whenever the section of track is free of obstacles, the reconstruction error takes small values (in blue in the figure). If an obstacle cuts one or more beams of the barrier, the similarity between the spaces decreases, and the reconstruction error increases suddenly over the threshold (in black in the figure), its value being proportional to the number of beams that are cut by the obstacle. The original covariance matrix has 36 eigenvectors, but in this case, only one eigenvector has been used in the final transformation, meaning a high redundant information reduction.

In the Figure 14 another situation appears when there is a random lack of radiation at the receivers. In this case, the reconstruction error is higher than the threshold during a time instant, but due to its short duration can be disregarded. Such is typical in the case of flying leaves, or the flight of birds inside the detection area.

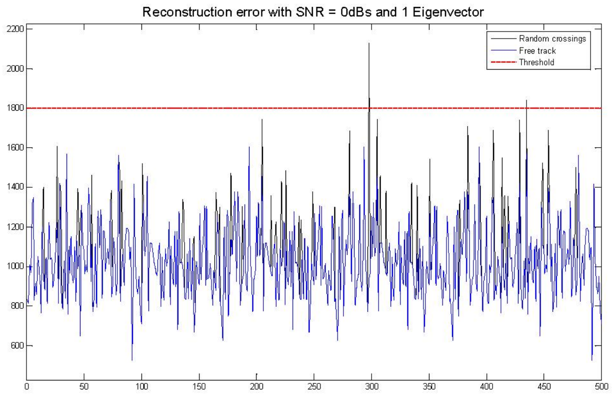

Fig. 14. Reconstruction error when there are random cuts.

The PCA process serves to increase the reliability of the objects detector, as a more accurate detection can be made of obstacles occurring in the supervised area.

VI. CONCLUSIONS

A proposal of a system for obstacle detection in railways has been carried out. The codification technique based on MO sets of sequences provides a high immunity against the infrared channel degradation. A prototype has been designed to test the feasibility of the codification.

Typical false alarms have been analyzed, and several solutions have been proposed to reduce such false alarms based on Kalman and *minimax* filtering. If we have some previous knowledge of the statistical noise, Kalman Filter works properly. Better results have been obtained with *minimax* filtering, when there is no information about the channel noise and when the worse case of estimation error needs to be minimized in order to increase railway safety.

Since there is a big amount of correlated information in the sensorial system, Principal Component Analysis has been proposed to reduce such information. Results show that this technique is appropriate to validate the obstacle detection and increases the reliability of the system.

Though simulations show the feasibility of the proposed solutions, a new prototype is being implemented to perform real outdoor tests, using the algorithms previously mentioned in this work.

VII. ACKNOWLEDGMENT

The work described in this paper has been possible by funding from the Ministry of Science and Technology - Projects SILPAR (reference DPI2003-5067) and PARMEI (reference DIP2003-08715-C02-01)- and the University of Alcalá through the ISUAP project (ref. PI2004/033).

VIII. REFERENCES

[1] http://www.laseroptronix.com/rail/

[2] http://www.smartmicro.de/computer_vision.html

[3] Juan Garcia, Cristina Losada, Felipe Espinosa, Jesús Ureña, ÁLvaro Hernández, Manuel Mazo, Ana Jiménez, Emilio Bueno, Carlos De Marziani, Fernando Álvarez, "*Dedicated Smart IR Barrier for Obstacle Detection in Railways*". IEEE Industrial Electronics Society, IECON 2005. 6-10 november 2005.

[4] J.Jesús García, Jesús Ureña, Álvaro Hernández, Manuel Mazo, J.Carlos García, Fernando Álvarez, J. Antonio Jiménez, Patricio Donato, Carmen Pérez."IR sensor array configuration and signal processing for detecting obstacles in railways" *Third IEEE Sensor Array and Multichannel Signal Processing Workshop SAM'04*.

[5] Tseng, C.-C. and Liu, C.L.: "Complementary Sets of Sequences", *IEEE Trans. Inform. Theory*, vol. IT-18, No. 5, Sep. 1972, pp. 644-652.

[6] Shu-Ming Tseng; Bell, M.R.; "Asynchronous multicarrier DS-CDMA using mutually orthogonal complementary sets of sequences", *IEEE Transactions on Communications Volume 48*, Issue 1, Jan. 2000 Page(s):53 – 59

[7] Fernando J. Álvarez, Jesús Ureña, Manuel Mazo, Álvaro Hernández, Juan J. García, José A. Jiménez y Patricio G. Donato. "Nuevo Algoritmo para la Generación Eficiente de Conjuntos de Cuatro Secuencias Complementarias" *TELEC'04 International Conference. Telecommunications, Electronics and Control.*

[8] Isaac I. Kim, Ron Stieger, Joseph A. Koontz, Carter Moursund, Micah Barclay, Prasanna Adhikari, John Schuster, Eric Korevaar, Richard Ruigrok, Casimer DeCusatis "Wireless optical transmission of fast ethernet, FDDI, ATM, and ESCON protocol data using the TerraLink laser communication system", *Optical Engineering*, Vol. 37 No. 12, December 1998

[9] Scott Bloom, AirFiber; Eric Korevaar, MRV Communications; John Schuster, Terabeam; Heinz Willebrand, LightPointe Communications, "Understanding the performance of free-space optics [Invited]" *Journal of Optical Networking*, June 2003, Vol 2 nº 6, pp 178-200

[10] Ken Dutton, Steve Thompson, Bill Barraclough, "The Art of Control Engineering", Addison-Wesley, 1997.

[11] Shen, X and Deng, L. "Game theory approach to discrete H∞ to filter design ". IEEE Trans. on signal processing. Vol 45, nº 4, April 1997.

[12] Simon, D. "To game theory approach to constrained minimax state estimation ". Report of the Department of Electrical Engineering, Cleveland State University. January, 2005.

[13] Simon, D. "From here to infinity ". Embedded Programming Systems. July, 2000.

[14] Turk, M., Pentland, A., "Eigenfaces for recognition", Journal of Cognitive Neuroscience, Vol. 3, pp. 72-85, 1991.