Identification of Loitering Human Behaviour in Video Surveillance Environments

Héctor F. Gómez A.[1(✉)], Rafael Martínez Tomás[2], Susana Arias Tapia[1], Antonio Fernández Caballero[3], Sylvie Ratté[4], Alexandra González Eras[1], and Patricia Ludeña González[1]

[1] Instituto de Ciencias de la Computación. Escuela de Ciencias de la Computación, Universidad Técnica Particular de Loja, Marcelino Champagnat S/N, 1101608, Loja, Ecuador
hfgomez@utpl.edu.ec

[2] Dpto. Inteligencia Artificial. Escuela Técnica Superior de Ingeniería Informática, Universidad Nacional de Educación a Distancia, Juan del Rosal 16, 28040 Madrid, Spain

[3] Departamento de Sistemas Informáticos e Instituto de Investigación en Informática, Universidad de Castilla-La Mancha, 02071, Albacete, Spain

[4] Department of Software and IT Engineering. Université du Québec - École de Technologie Supérieure. 1100 Notre-Dame West, Montreal, Québec, H3C 1K3, Canada

Abstract. Loitering is a common behaviour of the elderly people. We goal is develop an artificial intelligence system that automatically detects loitering behaviour in video surveillance environments. The first step to identify this behaviour was used a Generalized Sequential Patterns that detects sequential micro-patterns in the input loitering video sequences. The test phase determines the appropriate percentage of inclusion of this set of micro-patterns in a new input sequence, namely those that are considered to form part of the profile, and then be identified as loitering. The system is dynamic; it obtains micro-patterns on a repetitive basis. During the execution time, the system takes into account the human operator and updates the performance values of loitering in shopping mall. The profile obtained is consistent with what has been documented by experts in this field and is sufficient to focus the attention of the human operator on the surveillance monitor.

1 Introduction

Modelling and automatic identifying human behaviour is an area that has been developed significantly over the last few years in artificial intelligence and artificial vision. The aim of this type of investigations corresponds to the social need for more security in particular, but also in general, in the form of automatic observation of behaviour, such as in the health sector. We worked under the assumption that it was possible to develop a system that emulated the ability of an expert in recognizing loitering behaviour by considering a set of repeated actions (micro-patterns) that are part of the loitering profile. This system updates the

J.M. Ferrández Vicente et al. (Eds.): IWINAC 2015, Part I, LNCS 9107, pp. 516–525, 2015.
DOI: 10.1007/978-3-319-18914-7_54

profile with the contribution of a human operator, with the aim of covering the widest possible positive cases. The system is interactive and dynamic, because it enables interaction between the system and the human operator and because it facilitates the updating of the loitering profile.

We worked with the Generalized Sequential Patterns (GSP) algorithm to obtain the micro-patterns (patterns comprised of a small number of sufficiently repeated events). Srikant and Agrawal [1] use GSP to obtain sequential patterns based on data about consumer shopping habits at supermarkets. In our study, we had to change the input sequences of shopping behaviour to input sequences of labelled loitering activities from video surveillance to obtain micro-patterns that characterized the target behaviour. These micro-patterns constituted the loitering profile for identifying loitering behaviour in video surveillance domains. These micro-patterns are initially identified by positive sequences and loitering characteristics. Afterwards, a sensitivity analysis is performed on new cases of loitering sequences. Another step is the testing phase, which enables us to determine the appropriate percentage of inclusion for this set of micro-patterns in a new input stream. Since the system is dynamic, it obtains micro-patterns on a repetitive basis; the sensitivity analysis is continually updated too. During the execution time, the system takes into account the human operator annotations and updates the performance values.

The next section presents a review of works related to the learning and sequential micro-pattern recognition of human behaviour. After, we describe the proposed system based on micro-pattern matching with GSP and the selection of those micro-patterns that best characterized (profile) the target situation. Section 4 provides details of the experiments and the last section of the article consists of our conclusions and also proposes new areas of related research.

2 Related Work

Park, et al. [2] use a probabilistic scoring function to calculate the temporal similarity of event sequences with behavioural patterns that are defined as a priori, that is, they identify Daily Living Activities (DLA) of people at home, such as reading, listening to music, etc. Their approach consists of identifying previously known behaviour using more explicit knowledge.

In our research, we examined the repetition of the occurrence of an event, or several events, that led to the expected behaviour. Robertson, et al. [3] for example, use rules of behaviour with a probabilistic algorithm, namely the Hidden Markov Model (HMM), which identifies the behaviour of pedestrians crossing a street in various situations such as when there is a lot of traffic, or when the traffic lights change, etc. Other studies (e.g., see [4–6]) identify the behaviour of people in video images based on the recognition of human movements. For example, a sequential analysis of events was used with HMM to detect domestic accidents, and to identify health problems such as feinting and cardiac arrests, etc.

Chikhaoui et al. [7] use GSP to search behavioural patterns of persons during their daily routines with the objective of distinguishing individual behaviour.

The results show that there are clear differences between individual and typical behaviour of people in activity day live. Moreover, it is relatively easy to model normal behaviour. For example, the daily activity of a person at home in the morning is often the same, and can thus be modelled a priori [8]. We believe this proposed approach is innovative and has the potential of opening investigation into adjacent domains of research, such as in healthcare and psychology. However, this proposal is not an attempt to replace the human operator who monitors peoples behaviour; instead, it should be viewed as a practical alternative for preventing delinquent behaviour using state of the art surveillance technology (GSP and sensitivity analysis).

3 Loitering Behavior Identification Based on Sequential Micro-Patterns

It shows the methodological structure of both stages or scenarios of our proposal: the a priori training/learning process and the identification of patterns (Fig.1), and the stage when the system is in operation (Fig. 2).

In the training stage (Fig. 1), the first step (1) is to find micro-patterns using GSP. As mentioned in the introduction, micro-patterns are small patterns comprised of several sufficiently repeated events of loitering behaviour. In order to obtain these, we must have a series of positive case sequences. Each sequence represents the behaviour of a person and is obtained by labelling the individual activities of the monitored person for each second of video surveillance, e.g. walk, walk, stop, stop, walk, walk, stop, stop. It may be assumed that vision algorithms can recognize these events (see [6, 8–10]), or that they can be labelled manually or semi-manually.

To obtain the micro-patterns, GSP searches all frequent sequences in the database. Frequent sequences are those whose frequency exceeds a threshold value known as minimum support. In first stage, GSP searches for these frequent

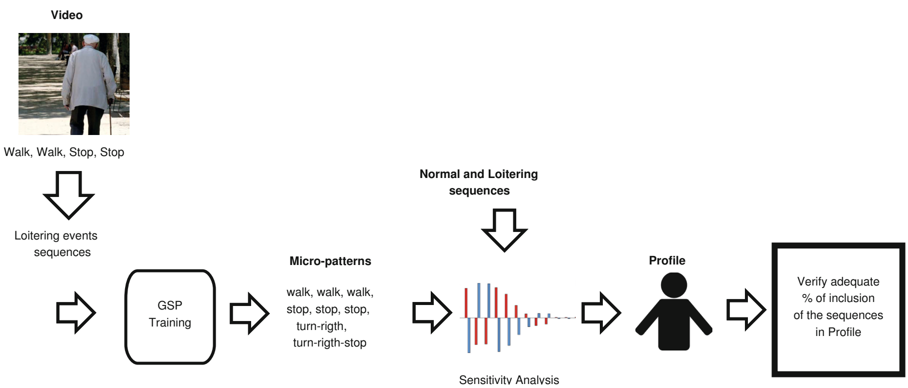

Fig. 1. Identify loitering human behavior: Training stage

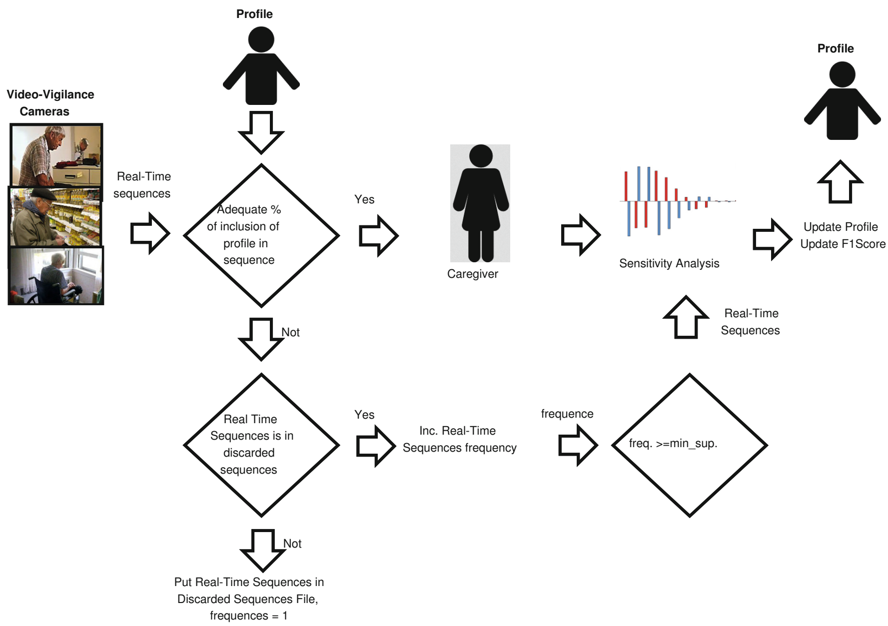

Fig. 2. Identify loitering human behavior: Test stage

sequences in the database (using hashing tree algorithm) from the sequences of size 1 (a sequence that contains 1 item), with 1-sequence frequent (candidate sequences); and from these, GSP builds sequences with size 2 (a sequence composed of 2 items) and select the frequent 2-sequence. Frequent 2-sequences (candidate sequences) are joined with frequent 1-sequences in order to form sequences of size 3. With these sequences, other sequences of higher orders are generated. GSP search ends when there are sequences of a desired length that appears more frequently in the database. Finally, in the second stage, GSP removes non-candidate sequences and as such obtains frequent sequences, known in this study how micro-patterns . A sensitivity analysis is applied to all the micro-patterns. Then, the most reliable ones for the target situation are selected, which form a more representative behaviour profile (see Fig. 1). The sensitivity analysis of the micro-patterns is carried out as follows:

Recognize (match) a p micro-pattern in a new sequence (s) implies extracting an s sub-sequence from s, which is of the same length as p, and calculate the Levenshtein distance (L) [11, 12] between p and s. If L is less than the threshold α, there is therefore an occurrence with a positive result. This is repeated for all the s that form part of s. We defined the matching threshold (α) as in [13] (In this case, it is related to football strategies). This is done to determine when a micro-pattern appears in a sequence. The use of this threshold is justified since it is difficult for an entire micro-pattern to appear exactly in the new sequence, given the variability of behaviour (see [14, 15]).

Test the initial micro-patterns with new sequences (this time with positives and negatives). The micro-patterns were sorted according to their F1Score metric since we wanted to detect as many positives as possible without affecting the precision value (equilibrium). The most characterizing micro-patterns comprise the behaviour profile. Determine the appropriate inclusion percentage of a profile in a sequence. This process consists of determining which percentage of inclusion of the profile patterns in the input sequence provides better results, or best characterizes the behaviour, because as we can see from the test results in the following section, it is important to maintain equilibrium, seeing that if too high percentage of precision is required, the performance index is low. Once the system is activated, we can examine the loitering profile within the input sequences i.e. with the aim of generating a warning for the human operator.

In Fig. 2, we can see a diagram of the execution stage. During this stage, which begins with the processing of the images, the input sequences are obtained to verify whether any of them correspond to the loitering profile, and generate the corresponding warning for the human operator. Thanks to the intervention of the human operator, the system can learn in a continuous manner and not only during the training stage. The execution stage considered the following factors:

Where the frequency sequence did not reach a level greater than the minimal support it was discarded automatically. This is something, which occurs only in GSP (the training phase). Although these sequences were automatically discarded by the system, there is also a way of retrieving them. On the other hand, if the new sequences that are inputted into the system contain the discarded sequences, their frequency will increase. Moreover, if this sequence frequency reached a higher level than the minimal support, this sequence was determined to be a micro-pattern. Consequently, we needed to repeat the entire training phase and the sensitivity analysis again. Therefore, it could be concluded that whenever there was a new micro-pattern, there would also be other micro-patterns.

During the updating of the sensitivity analysis, we observed that it was necessary for the human operator to determine whether true positive or false negative cases were needed, or if, by default, neither of these options were required. Afterwards, the human operator updated the sensitivity analysis of micro-patterns, namely those that constituted the profile.

4 Experimentation

The experimentation dataset, training and testing, is comprised of the following: 35 loitering sequences from CAVIAR-Project [16] test-bed contain footage from a camera situated in a shopping centre alley (outside a shopping mall).

Loitering video observation and manual labelling of events: 100 video recordings of loitering behaviour, recorded by video surveillance systems, were analyzed. As with other previous examples, a security assistant observed each of the video recordings for 40 seconds (timestamp). Then, the observations were manually registered in a software program specially designed for this investigation.

The 135 positive sequences were obtained from a single file of input sequences for the GSP. Group (b) was created in the same way. We generated 100 sequences by labelling negative events. Finally, we obtained a dataset of 235 mixed sequences. By using the 135 positives sequences to train the GSP, we were able to obtain micro-patterns. The results showed that with the value MS = 0.4 (where 40% of the sequences include the micro-pattern) and $\alpha = 2$ (where the distance from the micro-pattern is less than or equal to 2), we were able to obtain the required micro-pattern data. The values that were obtained during the testing phase provided the most accurate results.

For the sensitivity analysis of loitering behaviour (see Table 1), we used 135 positive sequences with their respective number (100) of negative sequences. This procedure helped us to obtain micro-patterns in order to make the desired profile. Finally, we used the same sequences (235 sequences) to determine the optimal percentage of micro-patterns. By also having the micro-patterns appear in a sequence we were able to ensure that the sequence contained the profile of loitering behaviour, thus obtaining new F1Score:

Table 1. Sensitivity analysis of micro-patterns obtained with *GSP*

Micro-patterns	Precision	Recall	F1 Score
walks, walks, walks, stops, stops, stops, walks, walks, walks	0,85	0,94	0,89
stops, stops, stops, stops, stops, walks, turns-right, walks, walks, turns-right, walks	0,73	0,96	0,82
stops, stops, stops, walks, walks, walks, walks, stops, stops, turns-left, walks	0,71	0,96	0,81
stops, stops, stops, stops, walks, walks, walks, turns-right, turns-right, browses, browses	0,81	0,96	0,87
walks, walks, walks, stops, stops, stops, walks, walks, walks	0,85	0,94	0,89

As can be seen from the Table 2, the results with the highest values are observed when the sequences contain 75 % of the profile micro-patterns (see row highlighted in bold). These results are considered valid (see [15, 16]) for this study as they provide a high recall value and because the level of precision does not severely decrease, but instead gradually increases based on the fact that the input sequences contain the optimum number of micro-patterns. The optimum percentage (75 %) of inclusion of the micro-patterns in the input sequences is thus determined by the highest value of the F1Score (0.91).

It is worth highlighting the trend, that where there is a precision level of 0.64, this indicates that a greater number of false alerts are generated compared with the values of the last three rows of the table (0.93). This theory can be sustained when we examine what happens with a precision level of 1.00. Where there is an optimum precision level of 1.00, there will be minimal false alerts. The precision value and the recall value rise and fall alternately, i.e. where one value increases the other value decreases. The precision and recall values are mutually dependent and the F1Score shows the relationship between these values.

Table 2. Sensitivity analysis to determine the optimal percentage of inclusion in the profile

Percentage of inclusion in the profile	Precision	Recall	F1 Score
35	**0,64**	0,98	0,77
40	0,64	0,976	0,77
45	0,67	0,97	0,79
50	0,71	0,95	0,81
55	0,74	0,943	0,82
60	0,74	0,94	0,82
65	0,74	0,94	0,82
70	0,76	0,94	0,84
75	**0,89**	**0,94**	**0,91**
80	0,9	0,919	0,90
85	0,9	0,87	0,88
90	**0,93**	0,865	0,89
95	**0,93**	0,84	0,88
100	**0,93**	0,77	0,84

To explain this point further from a theoretical perspective, the system identifies the maximum number of loitering sequences (recall) in relation to the minimum number of false alerts (precision). Therefore, the equilibrium between precision and recall can be found where the F1Score is 0.91.

The experimentation found that if there is no equilibrium between these values (i.e. when the number of input sequences is too small to generate representative micro-patterns of loitering behaviour), we must increase the number of input sequences by labelling more video recordings. For this reason, it is essential to achieve equilibrium between precision and recall values.

Table 3. Performance results of micro-patterns (new test)

Micro-patterns	Precision	Recall	F1 Score
walks, walks, walks, stops, stops, stops, walks, walks, walks	0,64	0,94	0,76
stops, stops, stops, stops, stops, walks, turns-right, walks, walks, turns-right, walks	0,67	0,94	0,78
stops, stops, stops, walks, walks, walks, walks, stops, stops, turns-left, walks	0,73	0,91	0,81
stops, stops, stops, stops, walks, walks, walks, turns-right, turns-right, browses, browses	0,77	0,9	0,82
walks, walks, walks, stops, stops, stops, walks, walks, walks	0,64	0,94	0,76
stops, stops, stops, stops, stops, walks, turns-right, walks, walks, turns-right, walks	0,67	0,94	0,78
stops, stops, stops, walks, walks, walks, walks, stops, stops, turns-left, walks	0,73	0,91	0,81

To test whether our online system worked, we performed a final test to check the learning capacity of the system with 100 new positive and 100 new negative sequences. In this case (see Table 3), the sensitivity analysis did not generate new micro-patterns, as there were not any sequences that reached the minimum support level. Therefore, there did not exist sufficient changes in the sensitivity analysis to produce new micro-patterns. Although the sensitivity analysis could be updated, we still used the same micro-patterns. As we can see below, the F1 score remains high, and as with the example of loitering behaviour, the results confirmed the micro-pattern percentage inclusion of 75% (see Table 4).

Table 4. Sensitivity analysis to determine the optimal percentage of inclusion in the profile (new test)

Percentage of inclusion in the profile	Precision	Recall	F1 Score
35	0,56	0,66	0,60
40	0,62	0,64	0,62
45	0,66	0,67	0,66
50	0,67	0,67	0,67
55	0,67	0,67	0,67
60	0,67	0,72	0,69
65	0,67	0,72	0,69
70	0,7	0,74	0,71
75	**0,7**	**0,77**	**0,73**
80	0,7	0,7	0,7
85	0,7	0,68	0,68
90	0,66	0,61	0,63
95	0,74	0,53	0,61
100	0,87	0,53	0,65

The results from Table 1 and Table 4 (i.e. after updating the sensitivity analysis of the selected micro-patterns) show that the obtained profile is used to distinguish between normal and potential theft behaviour. Furthermore, with the sequences that were used in the experimentation stage, the proposed system is capable of distinguishing between normal and loitering behaviour, a problem that was not, however, resolved in [17]. Indeed, this finding constitutes another important contribution to our study.

5 Conclusions

In this paper, we aimed to test the hypothesis that there is a common denominator in loitering behaviour which human experts are capable of identifying, namely in determining target scenarios, but which, at the same time, may result in difficulties when actually defining them. Our subsequent approach to this problem consisted of generating automatic alerts for human operators based on the creation of a pre-selected loitering profile and the implementation of a sensitivity analysis.

There were occasional occurrences of false alerts during the testing phase. These false alerts may be reduced by obtaining the optimum percentage of inclusion of micro-patterns in the input sequences and by repeating the sensitivity analysis. However, the proposed system is designed in such a way that, theoretically once it is fully installed and operational, it would work on its own by automatically generating message alerts for the human operator, who, in turn, would take the necessary security action.

This entire process is based on the identification and labelling of what we call elementary or basic activities, namely events that are recognizable by artificial vision algorithms or intelligent sensory monitoring techniques (segmentation, targeting, tracking and classification). By using these labelled sequences, i.e. where loitering behaviour usually occurs, we can obtain sequential micro-patterns with the GSP algorithm. After doing a sensitivity analysis with sequences showing normal (negative) and loitering (positive) behaviour, the most characteristic micro-patterns were selected, thereby confirming the loitering behaviour profile.

During runtime, i.e. when an input sequence contains the optimal percentage of the profile, a message alert is raised for the human operator. The human operator would then confirm the true positives and mark the false negatives. This human interaction with the system therefore helps to update the sensitivity analysis of the profile. Moreover, in real time the results that are originally discarded can likewise be recovered if their frequency of occurrences reaches the minimum required level.

To test our hypothesis, we carried out an experiment on the identification of loitering behaviour in a shopping mall. This scenario was chosen because they represented situations that fulfilled the conditions of the main areas of gerontology i.e Alzheimer. In this case, we manually labelled the video recordings, thus facilitating the sequencing of event labels.

Our results strongly suggest, therefore, that the implementation of a micro-pattern profile in video surveillance situations helps in the prediction and prevention of loitering activity, thereby serving as a fundamental tool for the human operator.

Acknowledgements. The authors are grateful to the Spanish Ministerio de Economía y Competitividad / FEDER for their financial contribution through the projects TIN2010-20845-C03-01 and TIN2010-20845-C03-02.

References

1. Srikant, R., Agrawal, R.: Mining sequential patterns: Generalizations and performance improvements. In: Apers, P.M.G., Bouzeghoub, M., Gardarin, G. (eds.) EDBT 1996. LNCS, vol. 1057, pp. 3–17. Springer, Heidelberg (1996)
2. Park, K., Lin, Y., Metsis, V., Le, Z., Makedon, F.: Abnormal human behavioural pattern detection in assisted living environmets. In: 3rd International Conference on Pervasive Technologies Related to Assistive Environments (2010)

3. Robertson, N., Reid, I., Brady, M.: Automatic human behaviour recognition and explanation for CCTV video surveillance. Security Journal 21(3), 173–188 (2008)
4. Quian, H., Ou, Y., Wu, X., Meng, X., Xu, Y.: Support vector machine behaviour-based driver identification system. Journal of Robotics, 173–188 (2008)
5. Leo, M., Spagnolo, P., D'Orazio, R., Mazzeo, P., Distante, A.: Real-Time smart surveillance using motion analysis. Expert Systems 25(5), 314–337 (2010)
6. Cuchiara, R., Prati, A., Vezzani, R.: A multi-camera vision system for fall detection and alarm generation. Expert Systems 24(5), 334–345 (2007)
7. Chikhaoui, B., Wang, S., Pigot, H.: A new Algorithm Based on Sequential Pattern for person identification in ubiquitous environments. In: Proceedings of the Fourth International Workshop on Knowledge Discovery from Sensor Data, pp. 20–28 (2010)
8. Fern, X., Komireddy, C., Burnnet, M.: Mining Interpretable Human Strategies: A Case Study. In: 7th IEEE International Conference on Data Mining, pp. 475–480 (2007)
9. Chun, L.: Definition, detection, and evaluation of meeting events in airport surveillance videos. In: TRECVID Workshop (2008)
10. Charkraborty, B., Bagdanov, A., González, J., Roca, X.: Human action recognition using an ensemble of body-part detectors. Expert Systems (2011), doi:10.1111/j.1468-0394.2011.00610.x
11. Levenshtein, V.: Binary codes capable of correcting deletions, insertions, and reversals. Soviet Physics Doklady 10(8) (1966)
12. Hernández-Vela, A., Bautista, M., Perez-Sala, X., Ponce-López, V., Escalera, S., Baró, X., Angulo, C.: Probability-based dynamic time warping and bag-of-visual-and-depth-words for human gesture recognition in rgb-d. Pattern Recognition Letters 50, 112–121 (2014)
13. Iglesias, A.: Modelado Automático del Comportamiento de Agentes Inteligentes. PhD dissertation Universidad Carlos III Madrid, Spain (2010)
14. Pillai, J., Vyas, O.P.: Overview of itemset utility mining and its applications. International Journal of Computer Applications 5(11), 9–13 (2010)
15. Manganaris, S., Christensen, M., Zerkle, D., Hermiz, K.: A data mining analysis of RTID alarms. Computer Networks 34(4), 571–577 (2000)
16. CAVIAR-Project: CAVIAR Project (May 20, 2009), http://home-pages.inf.ed.ac.uk/rbf/CAVIAR
17. Williem, A., Vamsi, M., Boles, K., Wageeh, W.: Detecting Uncommon Trajectories. In: Digital Image Computing: Techniques and Applications, pp. 398–404 (2008)