Reject-Optional LVQ-Based Two-Level Classifier to Improve Reliability in Footstep Identification.

CONFERENCE PAPER · JANUARY 2004

DOI: 10.1007/978-3-540-24646-6_12 · Source: DBLP

4 AUTHORS:

Jaakko Suutala
University of Oulu

Susanna Pirttikangas
University of Oulu

Jukka Riekki
University of Oulu

Juha Röning
University of Oulu

Reject-optional LVQ-based Two-level Classifier to Improve Reliability in Footstep Identification ⋆

Jaakko Suutala, Susanna Pirttikangas, Jukka Riekki, and Juha Röning

Intelligent Systems Group, Infotech Oulu
90014 University of Oulu, Finland
E-mail: Jaakko.Suutala@ee.oulu.fi

Abstract. This paper reports experiments of recognizing walkers based on measurements with a pressure-sensitive EMFi-floor. Identification is based on a two-level classifier system. The first level performs Learning Vector Quantization (LVQ) with a reject option to identify or to reject a single footstep. The second level classifies or rejects a sequence of three consecutive identified footsteps based on the knowledge from the first level. The system was able to reduce classification error compared to a single footstep classifier without a reject option. The results show a 90% overall success rate with a 20% rejection rate, identifying eleven walkers, which can be considered very reliable.

1 Introduction

In this paper, experiments on recognizing walkers on a pressure-sensitive floor are described. Automatic recognition of occupants leads to personal profiling and enables smooth interaction between the environment and the occupant. It facilitates the building of intelligent environments that learn and react to the occupants' behaviour [1].

The idea of using footsteps to identify persons is not new. In [2] and [3] the identification based on small area sensors, measuring the *ground reaction force*, were reported. In our earlier experiments, Hidden Markov Models (initial study of three persons' footsteps) [4] and Learning Vector Quantization [5] (for eleven walkers) [6] were used in the identification of single footsteps, measured by utilizing the pressure-sensitive ElectroMechanical Film [7] (EMFi), as described in [6]. In both cases, the overall classification rate was 78%.

In this paper, a two-level classifier is introduced. It is based on the 0-reject classifier with a reject option developed in [8]. These authors base their classification and rejection on single input, while we use three consecutive input samples (footsteps) to make the final decision. When a person walks into the room, it takes less than three seconds to record three footsteps on the floor. This method improved the identification reliability, which is essential in building smart living room scenarios based on a personal profile.

2 The Reject-optional Learning Vector Quantization

In a complex classification problem, such as footstep identification, it is useful to reject samples that can not be classified reliably to any of the known classes. The aim is to

⋆ This work was funded by TEKES and Academy of Finland

reject the highest possible percentage of samples that would otherwise be misclassified. As a side effect, some correctly classified input samples are rejected, although they would be correctly classified without the reject option. In this section, the term 0-reject classifier is used to describe a classifier without a reject option.

To achieve the criteria for rejection, two different thresholds must be determined: one for detecting samples lying in an overlapping region, and one for the samples significantly different from the trained class boundaries. In our application, the overlap corresponds to a situation where two persons have similar features in their footsteps or the measurements are noisy. If the input sample is far from the class boundaries, a previously unknown (to the system) person is walking on the floor. To achieve the thresholds, reliability evaluators are calculated from the training data. This evaluator is derived from the properties of the 0-reject classifier. In this paper, an LVQ-based reliability evaluator and the main ideas for determining optimal thresholds are presented. More details can be found in [8].

The reject option can be adaptively defined for the given application domain. This is done by assigning a cost coefficient to the misclassified, rejected and correctly classified samples. Optimal thresholds can be computed using an effectiveness function for given cost values. The effectiveness function P is determined in a form

$$P = C_c(R_c - R_c^0) - C_e(R_e - R_e^0) - C_r R_r, \tag{1}$$

where C_c, C_e, and C_r are the costs for correctly classified, incorrectly classified and rejected samples. R_c^0 and R_e^0 are the percentages of correctly and incorrectly classified samples for a given threshold σ. R_c, R_e and R_r present the percentages of correctly classified, misclassified and rejected samples after the introduction of the reject option. The effectiveness function (1) needs to satisfy $C_e > C_r$.

The output vector of a trained LVQ classifier is the distance between the input sample and the closest prototype vector in a codebook, and is named as O_{WIN}. Moreover, a trained LVQ codebook presents the class boundaries of given training set and can be used to compute the values of reliability evaluators. The first reliability evaluator Ψ_a is defined as

$$\Psi_a = \begin{cases} 1 - \frac{O_{WIN}}{O_{max}}, & \text{if } O_{WIN} \leq O_{max} \\ 0, & \text{otherwise,} \end{cases} \tag{2}$$

where O_{max} is the highest value of O_{WIN} in the training set. This evaluator is used to eliminate samples significantly different from the trained codebook vectors. The second reliability evaluator Ψ_b is

$$\Psi_b = 1 - \frac{O_{WIN}}{O_{2WIN}}, \tag{3}$$

where O_{2WIN} is the distance between the input sample and the second winner prototype vector. This criterion is for rejecting the input samples belonging to an overlapping region.

The optimal value of reject threshold $\underline{\sigma}$ is obtained from the training set. The maximum of the effectiveness function can be found from the derivative for $P(\sigma)$ ([8]) as follows,

$$C_N D_e(\sigma) - D_c(\sigma) = 0, \tag{4}$$

where $D_c(\Psi_a)$ and $D_e(\Psi_b)$ are occurrence densities, and $C_N = (C_e - C_r)/(C_r + C_c)$ is normalized cost. The occurrence densities can be estimated using Eq. (2) and Eq. (3) for every training sample.

The following training algorithm presents the determination of the optimal threshold values $\underline{\sigma}_a$ and $\underline{\sigma}_b$ of fixed cost coefficients.

1. The training set is classified with a 0-reject classifier and then split into the subsets S_c of correctly classified samples and the subset S_e of misclassified samples.
2. The values of the reliability evaluators Ψ_a and Ψ_b are determined for each sample in the sets S_c and S_e. Then, the occurrence density functions $D_c(\Psi_a)$, $D_c(\Psi_b)$, $D_e(\Psi_a)$, and $D_e(\Psi_b)$ are calculated.
3. The values of σ_a and σ_b satisfying (4) are calculated.
4. The values of σ_a and σ_b from Step 3 maximizing (1) are chosen as rejection thresholds.

Figure 1 shows the typical occurrence densities for the footstep data. Samples below the given threshold σ_b are rejected.

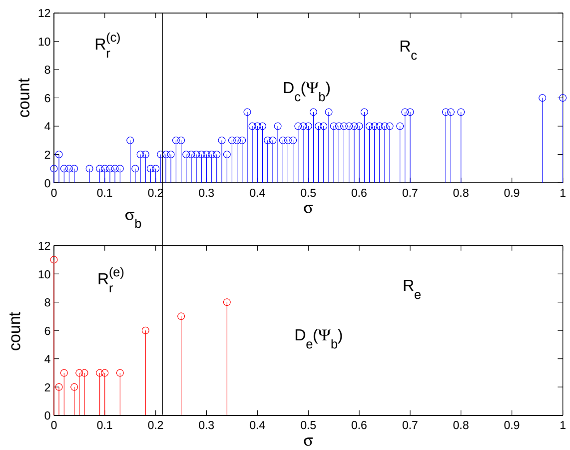

Fig. 1. The example occurrence densities $D_c(\Psi_b)$ and $D_e(\Psi_b)$ for correctly and incorrectly classified footstep data using a reliability evaluator Ψ_b. $R_r^{(c)}$ and $R_r^{(e)}$ are the percentages of rejected samples for a given threshold σ_b. R_c and R_e are the accepted samples of correctly and incorrectly classified samples by the reject classifier

3 Two-level Identification System

By combining decisions of multiple classifiers, we usually get more accurate results compared to the decision of one classifier. The combinations of classifiers are typically multi-level systems where several similar or different classifiers are used to to make a joint decision concerning the input patterns [9]. For example, an application using multiple independent LVQ classifiers to recognize handwritten digits can be found in [10].

In our system, three consecutive footsteps from one person are used in the identification. The architecture of the classifier is shown in Figure 2. The first level consists of two different reliability evaluators, Ψ_a and Ψ_b, as presented in section 2. Level 1 rejects footsteps if Ψ_a is below σ_a, or if Ψ_b is below σ_b. The decision at the second level is based on the knowledge of the classification results at level 1, and the final decisions are defined as

– REJECT
  1. If a majority of the three samples are rejected by Ψ_a.
  2. If one of the three samples is rejected by Ψ_a and another one is rejected by Ψ_b.
  3. If all samples are classified to different classes.
– ACCEPT
  1. If a majority of the samples are classified to the same class.
  2. If two of the samples are rejected by Ψ_b and one is classified to one of the classes.

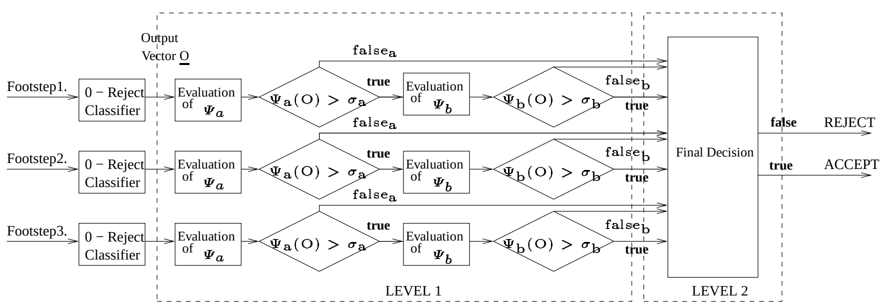

Fig. 2. Two-level identification system, which consists of two different reliability evaluators, Ψ_a and Ψ_b. Level 1 rejects footsteps if Ψ_a is below σ_a, or if Ψ_b is below σ_b. Level 2 rejects or accepts three steps pre-classified at the first level. At the second level, samples can be accepted if a majority of them belong to the same class or if two of them are rejected by σ_b (from the overlapping region) at the level 1

4 Experimental Results

The collected test data consist of the measurements of 11 persons walking on the pressure-sensitive floor, stepping on one particular stripe (containing about 40 footsteps / person). The data collection and processing, as well as the feature selection, are described more detailed in [6]. The rejection threshold determination algorithm and two-level identification system were implemented in the MATLAB technical language.

Table 1. The results of 10 randomly chosen data sets of eleven persons' footsteps. The cost coefficients of misclassification C_e and rejection C_r were selected as (2,1),(4,3),(6,5),(10,9),(15,14) and (-) (no rejection on the first level), keeping C_c equal to one. The first column presents the cost values of the best results. The second and third column consist of the best total recognition and reject rates of three consecutive footstep. The fourth and fifth columns present total recognition and reject rates using single footsteps, and the last column shows the recognition rates of a single 0-reject LVQ classifier

Test set	(C_e, C_r)	Recog. rate 3 footsteps	Reject rate 3 footsteps	Recog. rate 1 footstep	Reject rate 1 footstep	0-reject classifi er 1 footstep
1.	(-)	93.2	14.3	66.4	0.0	66.4
2.	(6,5)	84.8	21.4	67.8	10.7	67.2
3.	(15,14)	87.9	14.3	74.2	22.1	66.4
4.	(15,14)	88.6	9.5	75.7	21.4	70.2
5.	(-)	87.9	16.7	62.6	0.0	62.6
6.	(15,14)	100	21.4	75.4	14.5	70.2
7.	(-)	86.4	11.2	67.2	0.0	67.2
8.	(15,14	90.2	11.9	70.9	1.5	69.5
9.	(6,5)	95.5	30.9	69.2	10.7	68.0
10.	(15,14)	75.0	28.6	59.8	11.5	58.0
Average		89.0%	18.0%	68.9%	9.2%	66.6%

The two-level classifi er system was tested with 10 different, randomly selected groupings for the data. The LVQ codebook consisted of 7 prototype vectors for each class. The initial codebook training was similar to [6]. The reject thresholds were determined for each data set using different pairs of cost coeffi cients for misclassifi cation C_e and rejection C_r.

Different cost coeffi cients were tested to fi nd the optimal relation between the recognition and reject rates. The relations between C_e and C_r were chosen to be small, as it is essential to keep the percentages of rejection rate quite low. When the relation was raised, it turned out that a majority of the samples were rejected. Using (C_e, C_r) = (2,1), for example, the average reject rate was 65% due to the huge overlap between the different classes.

The best results from these 10 randomly generated data sets are shown in Table 1. The results show that the two-level reject-optional LVQ for three footsteps was able to improve identifi cation compared to the single footstep classifi cation. The average rate shows 89.0% recognition by the two-level classifi er with a 18.0% reject rate,while the single-step classifi er gives only 68.9% and 66.6% average rates with and without a reject option, respectively. The most general cost coeffi cients C_e and C_r of the best results were 15 and 14. The typical rejection thresholds for using these costs were $\sigma_a = 0.5$ and $\sigma_b = 0.06$.

5 Conclusions

In this paper, experiments on identifying persons based on their successive footsteps on an EMFi floor were reported. A two-level identifi cation system was developed for decision-making. The system utilizes a reject option for single footsteps and makes a decision on identification based on three consecutive footsteps. Footsteps can be recorded when a person enters the smart living room within three seconds at best.

The reject option and the two-level classifier were able to raise the recognition rates compared to the single-footstep classification. The overall success rate was 89%, and the rejection rate was 18%. It is essential to make the identification as reliable as possible, as the room is supposed to react to the users identity and presence. The number of testees in this experiment was eleven, but in a smart living room scenario is considered, probably fewer occupants are about to use the space. Then, the overall recognition rate might be even better.

Naturally, this research aims at real-time learning and identification. The reject option provides a possibility to enable adaptiveness. The reason for rejecting an identification can be determined based on the algorithm. The thresholds calculated (σ_a, σ_b) explicitly indicate if the person is unknown to the system, or if the rejection is based on noisy measurements. If identification is rejected based on σ_a, the system can interpret the occupant as a new person and start retraining the classifier automatically based on the new footsteps.

References

1. I. A. Essa. Ubiquitous sensing for smart and aware environments: Technologies towards the building of an aware home. *IEEE Personal Communications*, October 2000. Special issue on networking the physical world.
2. M.D. Addlesee, A. Jones, F. Livesey, and F. Samaria. ORL active floor. *IEEE Personal Communications*, 4(5):35–41, October 1997.
3. R.J. Orr and G.D. Abowd. The smart floor: A mechanism for natural user identification and tracking. In *Proc. 2000 Conf. Human Factors in Computing Systems (CHI 2000)*, New York, 2000. ACM Press.
4. S. Pirttikangas, J. Suutala, J. Riekki, and J. Röning. Footstep identification from pressure signals using Hidden Markov Models. In *Proc. Finnish Signal Processing Symposium (FINSIG'03)*, pages 124–128, May 2003.
5. T. Kohonen. *Self-Organizing Maps*. Springer-Verlag Berlin Heidelberg New York, 1997.
6. S. Pirttikangas, J. Suutala, J. Riekki, and J. Röning. Learning vector quantization in footstep identification. In M.H. Hamza, editor, *Proc. 3rd IASTED International Conference on Artificial Intelligence and Applications (AIA 2003)*, pages 413–417, Benalmadena, Spain, September 8-10 2003. IASTED, ACTA Press.
7. M. Paajanen, J. Lekkala, and K. Kirjavainen. Electromechanical film (EMFi) - a new multipurpose electret material. *Sensors and actuators A*, 84(1-2), August 2000.
8. C. De Stefano, C. Sansone, and M. Vento. To reject or not to reject: That is the question - an answer in case of neural classifiers. *IEEE Transactions on Systems, Man, and Cybernetics-part c: Applications and Reviews*, 30(1):84–94, February 2000.
9. J. Kittler, M. Hatef, R.P.W. Duin, and J. Matas. On combining classifiers. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 20(3):226–239, March 1998.
10. T. K. Ho. Recognition of handwritten digits by combining independent learning vector quantization. In *Proceedings of the Second International Conference on Document Analysis and Recognition*, pages 818–821, October 1993.