Learning Vector Quantization in Footstep Identification

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ABSTRACT

This paper reports experiments on recognizing walkers from measurements with a pressure-sensitive floor, more specifically, a floor covered with EMFi material. A 100 square meter pressure-sensitive floor (EMFi floor) was recently installed in the Intelligent Systems Group's research laboratory at the University of Oulu as part of a smart living room. The floor senses the changes in the pressure against its surface and produces voltage signals of the event. The test set for footstep identification includes EMFi data from 11 walkers. The steps were extracted from the data and featurized. Identification was made with Learning Vector Quantization. Discarding a known error type in the measurements, the results show a 78 % overall success rate of footstep identification and are hence very promising.

KEY WORDS
Intelligent Environments, Personal Profiling

1 Introduction

The research on intelligent environments [1], [2], [3] aims at making smart houses, offices, tourist attractions etc., where the environment learns and reacts to the behaviour of the occupants. The methodology can be applied in homes for the elderly and disabled as an enabling technology for monitoring hazardous situations as well as in surveillance systems or in child care. Automatic recognition of the occupants without a need for wearable sensors leads to personal profiling and enables smooth interaction between the environment and the occupant.

In this paper, experiments on recognizing walkers on a pressure-sensitive floor are described. The classification of footsteps was done with Learning Vector Quantization. The EMFi material installed under the laboratory floor during the building stage was used in making the measurements.

The idea of using footsteps to identify persons is not new. Hidden Markov Models and Nearest-Neighbor classification have been used in recognizing walkers and applied in [4], and [5], respectively. The difference compared to our research is the utilization of dissimilar sensors that measure the vertical component of the *ground reaction force* caused by the weight and inertial forces of the body. Furthermore, the other studies have had only small areas covered with sensors throughout the floor which is capable of measuring the steps, while we have the whole floor area capable of measurement. In our initial experiments, Hidden Markov Models were used in the identification [6], but in this paper, Learning Vector Quantization is used.

In the next section, the EMFi material and the layout of the testing area are introduced. In section 3, the basic characteristics of Learning Vector Quantization are presented. The data set collected and the preprocessing are described in section 4. The test results are presented in section 5. Finally, some conclusions are drawn and future work is clarified.

2 EMFi Material

ElectroMechanical Film [7] (EMFi) is a thin, flexible, low-price electret material, which consists of cellular, biaxially oriented polypropylene film coated with metal electrodes. In the EMFi manufacturing process, a special voided internal structure is created in the polypropylene layer, which makes it possible to store a large permanent charge in the film by the corona method, using electric fields that exceed the dielectric strength of EMFi. An external force affecting the EMFi surface causes a change in the film's thickness, resulting in a change in the charge between the conductive metal layers. This charge can then be detected as a voltage. EMFi is a Finnish innovation and a trademark of EMFiTech Ltd.

EMFi material has been used for many commercial applications, such as keyboards, microphones in stringed musical instruments and small and large area sensors. A Finnish company, Screentec Ltd, has developed vandal-proof keyboards and keypads using EMFi foil protected by a steel or plastic plate. EMF Acoustics Ltd has produced EMFi-based microphones for different stringed instruments, such as bass guitars, acoustic guitars and violins.

EMFi material has been installed in the Intelligent Systems Group's (ISG) research laboratory at the University of Oulu. The covered area is 100 square meters. The EMFi floor in the ISG laboratory is constructed of 30 vertical and 34 horizontal EMFi sensor stripes, 30 cm wide each, that are placed under the normal flooring (see Figure 1). The stripes make up a 30x34 matrix with a cell size of 30x30 cm. Instead of simply installing squares of EMFi material under the flooring, stripes were used, be-

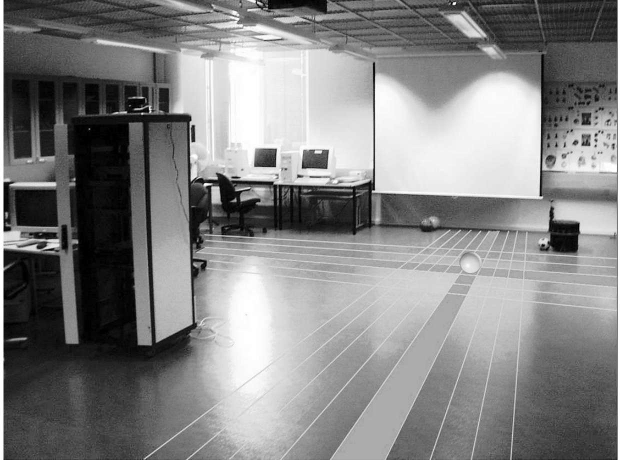

Figure 1. The setting for EMFi sensor stripes under the laboratory's normal flooring.

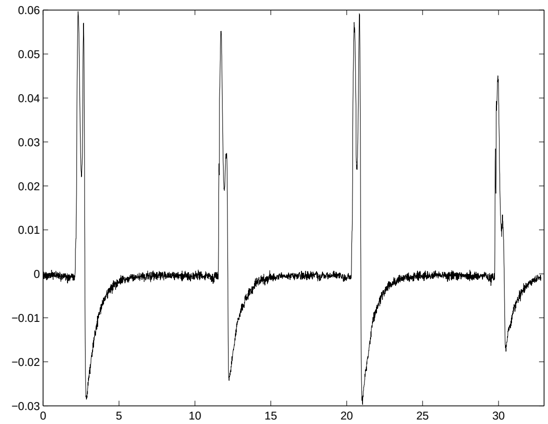

Figure 2. Raw EMFi data from one stripe. The x-axis represents time in seconds and the y-axis voltage.

cause this layout requires clearly less wiring. If squares were installed, the number of wires would be over a thousand. If a smaller room were to be covered with EMFi material, squares could be used. This would make it easier to determine the locations of the occupants in the room.

Each of the 64 stripes produces a continuous signal that is sampled at a rate of 100Hz and streamed into a PC, from where the data can be analyzed in order to detect and recognize the pressure events, such as footsteps, affecting the floor. The analogous signal is processed with a National Instruments AD card, PCI-6033E, which contains an amplifier. It would be possible to increase the sampling frequency up to 1.56kHz, but 100Hz was considered adequate for this application.

3 Learning Vector Quantization

Learning Vector Quantization (LVQ) [8] is a well known tool in various applications where statistical classification is needed such as texture analysis [9], speech recognition [10], and image analysis [11], to name a few. LVQ algorithms classify the data based on piecewise linear class boundaries, which are determined by supervised learning. In this paper, the Optimized-Learning-Rate LVQ1 (OLVQ1) was used, and it is briefly described. For more information on LVQ algorithms [8] is recommended.

Consider the samples c derived from a finite set of classes $\{C_k\}$. In LVQ, a subset of codebook vectors are assigned to each class C_k. Then, each c is set to belong to the same class as the closest (in Euclidean sense) codebook vector m_i. Let $j = \arg\min_i\{||c - m_i||\}$ define the index of the nearest m_i to c. The equations below define the basic LVQ1 algorithm.

$$\begin{aligned} m_j(t+1) &= m_j(t) + \alpha(t)[c(t) - m_j(t)] && (1) \\ m_j(t+1) &= m_j(t) - \alpha(t)[c(t) - m_j(t)] && (2) \\ m_i(t+1) &= m_i(t), \text{for } i \neq j, && (3) \end{aligned}$$

where $0 < \alpha(t) < 1$, and $\alpha(t)$ is the learning rate, which decreases with time. The algorithm minimizes the rate of misclassification error by iteratively updating the codebook vectors at times $t = 0, 1, 2, \ldots$. Eq. (1) is used if c and m_j belong to the same class, and Eq. (2) if c and m_j belong to different classes.

In optimized LVQ1, attention is payed on the learning rate $\alpha(t)$, and it is determined optimally for fastest convergence. To achieve this, the equations above are expressed as

$$m_j(t+1) = [1 - s(t)\alpha_j(t)]m_j(t) + s(t)\alpha_j(t)c(t), \quad (4)$$

where $s(t) = +1$ if the classification is correct, and $s(t) = -1$ if the classification is wrong. Then, it can be shown that the optimal learning rates are determined by the recursion

$$\alpha_j(t) = \frac{\alpha_j(t-1)}{1 + s(t)\alpha_j(t-1)}. \quad (5)$$

In this work, the LVQ_PAK [12] developed at the Faculty of Information Technology at Helsinki University of Technology, was used for creating the codebook for classification.

4 Data

The data were collected in the spring 2003 and consist of the measurements of 11 persons walking on the pressure-sensitive floor. The testees stepped on one particular stripe, and wore shoes. Footsteps targeted into the crossing of two stripes were collected as well. Furthermore, stepping with the right foot and the left foot were separated. Also, in one test, footsteps without shoes were collected. All in all, about 60 footsteps were collected from each testee.

During the test, all of the 64 EMFi stripes produce noisy data (see Figure 2, which shows the data recorded from one channel during the test). The footsteps must be identified and segmentated from noisy channel data.

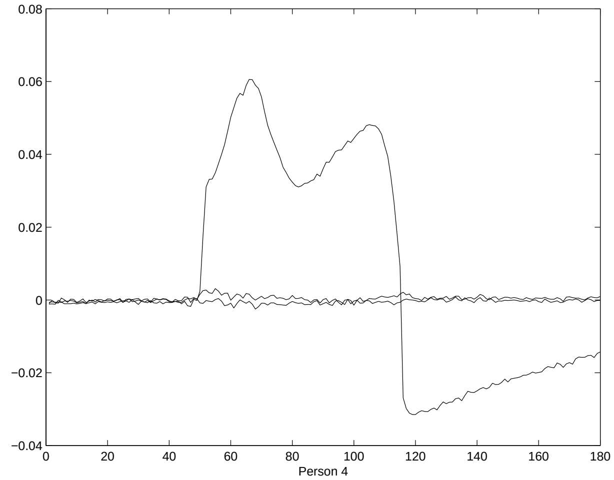

Figure 3. A good-quality step.

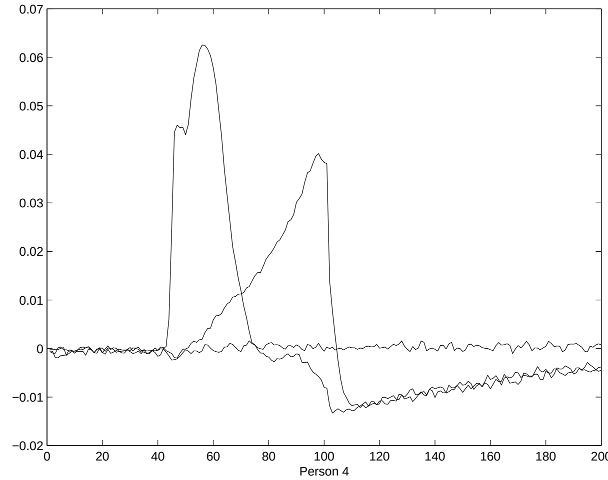

Figure 5. A footstep in the crossing of two stripes.

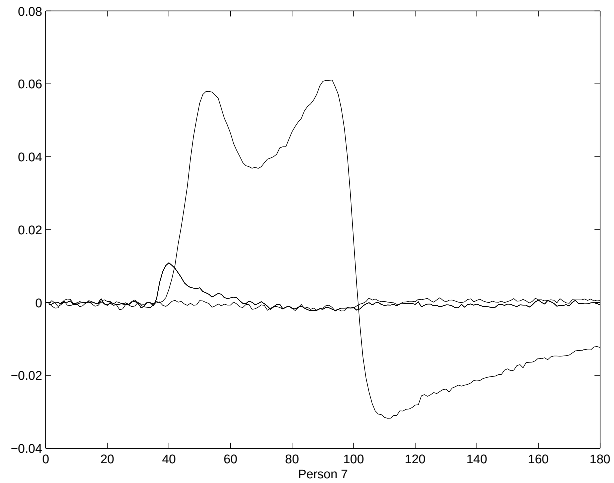

Figure 4. A footstep that hits mainly on one stripe, but a small fraction of the step affects the measurements of an adjacent channel.

The segmentation problem is being studied in a different project. The amplitude of a step is very large compared to signal noise variance, and no filtering of the noise is therefore needed.

Different problems arise in finding "good-quality" steps for modelling. In Figures 3, 4, 5, and 6 different situations occurring while walking are presented. In these figures, the measurements from three adjacent channels are shown.

In Figure 3, a good-quality step is shown. The step is hit on the center of one stripe. The footstep in Figure 4 is targeted mostly onto one stripe, but a small amount of the step is hit on another stripe. In Figure 5, the center of the footstep (between the ball and the heel of the foot) has hit the crossing of the two stripes. In Figure 6, several successive footsteps are hit on one stripe. In other words, this is the situation when a person walks along one stripe. From Figure 6, it can be seen that in this case the resetting time of the EMFi floor causes the steps to blur into each other, and they cannot be used in modeling.

The problems mentioned earlier affect the selection of the signal segmentation algorithm. In this initial phase, raw segmentation was made with hybrid-median filters [13]. The steps depicted in Figure 6 were rejected, and for the other cases, footsteps were generated by summing the measurements from adjacent channels to obtain the whole footstep.

The data was divided into a training set and a test set. In this classification experiment, the footsteps from both left and right foot were used. The training set consisted of 272 footsteps (around 20-26 examples for each class), and the test set consisted 131 footsteps.

For feature selection, the footsteps were divided into two sections: the ball of the footstep and the heel of the footstep. The partition was made according to the local minimum (x_{min}, y_{min}), as shown in Figure 7. A software package LNKnet [14] developed at MIT Lincoln Laboratory was used in feature selection. Several features were derived from footstep data (including spatial and frequency domain features), and they were tested with the kNN- classifier in LNKnet.

The features chosen for classification are the length from x_{start} to x_{end}, the amplitude means and standard deviations for the ball of the foot (from x_{start} to x_{min}), and for the heel of the foot (from x_{min} to x_{mid}). Furthermore, the coordinate points (x_{max1},y_{max1}), (x_{min}, y_{min}), (x_{max2}, y_{max2}), the amplitude y_{end}, and an average $[(y_{max1} - y_{min}) + (y_{max2} - y_{min})]/2$ were chosen.

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11
P1	84.62	8.34	38.10	0.00	0.00	9.09	0.00	0.00	0.00	0.00	0.00
P2	7.69	83.33	9.52	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
P3	0.00	0.00	33.33	0.00	0.00	0.00	0.00	25.00	0.00	0.00	0.00
P4	0.00	0.00	0.00	91.67	0.00	0.00	16.67	0.00	0.00	8.33	0.00
P5	0.00	0.00	0.00	8.33	69.23	9.09	25.00	0.00	0.00	0.00	0.00
P6	0.00	0.00	0.00	0.00	0.00	72.73	8.33	0.00	0.00	16.67	0.00
P7	0.00	0.00	0.00	0.00	7.69	0.00	25.00	8.33	0.00	8.33	25.00
P8	0.00	8.34	19.05	0.00	15.39	0.00	0.00	66.67	10.00	0.00	0.00
P9	7.69	0.00	0.00	0.00	0.00	0.00	25.00	0.00	90.00	8.33	0.00
P10	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	58.33	8.33
P11	0.00	0.00	0.00	0.00	7.69	9.09	0.00	0.00	0.00	0.00	66.67

Table 1. Confusion matrix for the eleven persons' footsteps.

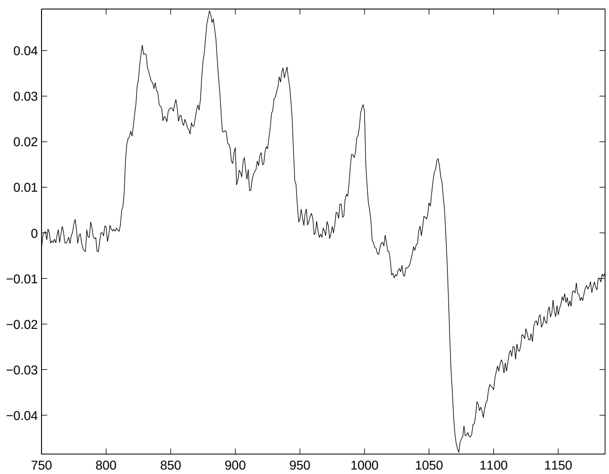

Figure 6. Several successive footsteps on one stripe.

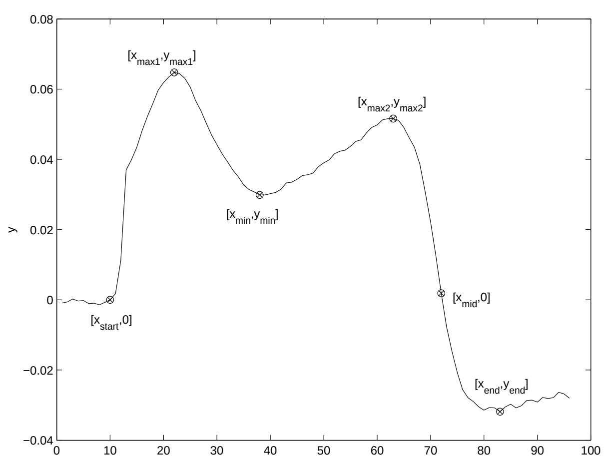

Figure 7. The features derived from each footstep.

5 Test Results

The best results were obtained with a codebook size of 60. The OLVQ1 was run for 100 iterations, and the LVQ1 for 1000 iterations. The results are presented in Table 1. There is notable confusion in the footsteps of the persons number 3, 7, and 10. The overall recognition accuracy is 66%.

In Figure 4, the footstep from testee number 7 is shown. The footstep in Figure 4 has not completely hit only one stripe, but in a small extent it reaches the adjacent stripe as well. In studying the results, it was noticed, that almost all footsteps from the poorly identified walkers were of the same kind. Classification was successful for the footsteps alike the one shown in Figure 5.

Therefore, the reason for the badly identified walkers is in the summing process made before classification. The measurements from adjacent channels were summed to achieve the whole footstep. The summing works, if the step is hit in the center of the two stripes. If only a small part of the step hits on the other stripe, the summing affects the coordinate points of the maximum to change into another location, and in this case, the classification is not reliable. If these situations are ignored, the overall recognition accuracy is 78%.

6 Conclusions

In this paper, experiments on identifying persons based on their footsteps on an EMFi floor were reported. The results are very promising, but there are still unanswered questions. In this phase, the basic tools for using the EMFi floor are being developed.

The features chosen for modelling seem to capture the signal characteristics, but the summation of the measurements from adjacent channels is not the solution for producing the whole footstep. The summation works, if the step is divided evenly between two stripes. This way, the chosen features, such as coordinate points for the maximum, are not confused. If there is only a small fraction, that hits the other stripe, the summation worsen the classification results. It is possible to divide the footsteps into good-quality steps and into bad-quality steps based on reasons mentioned above. The misbehaved footsteps can be either ignored or sensor fusion can be used in footstep reconstruction. If the badly formulated footsteps are cleared from the test set, an 78 % overall recognition rate can be achieved.

Naturally, this research aims at real-time learning and identification. The goal is to find a way to learn the footsteps from a person immediately one walks into the room. Furthermore, the person needs to be identified from the first steps he produces on the floor.

The problem of identification will be even more difficult with several persons walking in the room at the same time. This requires a methodology for tracking objects on the floor, and this will be studied in a different setting later on.

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