# Baby-Posture Classification from Pressure-Sensor Data

Sabri Boughorbel, Fons Bruekers, Jeroen Breebaart
*Philips Research Laboratories*
*5656 AE Eindhoven, The Netherlands*
*{Sabri.Boughorbel, Fons.Bruekers, Jeroen.Breebaart}@philips.com*

## Abstract

*The activity of babies and more specifically the posture of babies is an important aspect in their safety and development. In this paper, we studied the automatic classification of baby posture using a pressure-sensitive mat. The posture classification problem is formulated as the design of features that describe the pressure patterns induced by the child in combination with generic classifiers. Novel rotation invariant features constructed from high order statistics obtained from the concentric rings around the center of gravity. Non-constant ring radii are used in order to ensure uniform cell areas and therefore equal importance of features. A vote fusion of various generic classifiers is used for classification. Temporal information was shown to improve the classification performance. The obtained results are promising and open new opportunities for applications and further research in the area of baby safety and development.*

## 1. Introduction

Child development is an extensive field of research that covers many aspects such as, e.g., psycho-social, cognitive, physical, health, and linguistic development. Many research studies have been conducted in these areas and have shown a high correlation in the different developmental aspects of children [1]. When a child starts speaking few words he has often also reached a certain physical development such as the ability to walk, indicating certain movement and balance skills. The posture of the child during his daily activity can provide valuable information on his development. The abilities to roll over, sit, crawl and stand are well known milestones for the development of the babies. Besides development, posture is also relevant to assess the comfort and safety of a child. Knowing the posture of the child can be useful during sleep to correct the sleeping posture and help to prevent SIDS (sudden infant death syndrome). At a higher level, the posture of the child can also give an indication on the child's mental activity or status. For instance, lying on the back while being very quiet could indicate the child is willing to sleep. Sitting and being quiet could indicate that the child is, e.g., concentrated on a toy, watching TV. In summary, automatic posture classification is an interesting element of a system that supports parents to monitor their children by providing the parents with feedback and summaries on the sleep and day activities. Automatic posture classification can be relevant for other applications such as preventing pressure sores (decubitus) for elderly and monitoring sleep problems [2][3].

The topic of posture classification based on pressure data has been mainly researched for applications related to sitting and sleeping. In [4] 18 sitting postures have been classified using PCA. In [5] 8 sleeping postures have been classified from pressure data based on kurtosis and skweness estimation. The automatic posture classification of babies has not been extensively addressed in the literature. One of the popular approaches is to use a camera. However, many drawbacks can be expected using computer vision approaches. The setup of a camera is always difficult since it requires adjustment each time the location of the baby has changed. Moreover, the usage of computer vision techniques to analyze the posture of babies is rather difficult problem since, e.g., the viewing angle, lighting condition, baby clothing can drastically change during a normal usage of the system. Additionally, placing a camera in the home is considered by many people as a privacy threat. In [6] a system using a pressure mat can detect the level of activity i.e., quiet, moving, crying by modeling the kinetic energy and supine and prone postures for young babies by counting the number of pressure blobs. The BabySense described in [7] comprises soft, pressure sensitive foam which detects the presence, motion and types of activity of babies i.e., sitting, standing and playing and transmits the results to a remote display. Unfortunately it is not described in the paper how the activity and posture can be recognized.

In this work, we used a set of 4 Tekscan pressure-sensitive flat mats of a total size 84x96 $cm^2$ with one sensor cell per $cm^2$ to measure the pressure pattern of a baby during normal activity. The frame rate was adjusted to 25 fps. The pressure data was first pre-processed then features were extracted and finally posture classification was performed. In Section 2, we introduce novel rotation invariant features. In Section 3, we describe the classification procedure. In Section 4, we provide experimental results and benchmarks, finally, we give a conclusion and recommendations for future work.

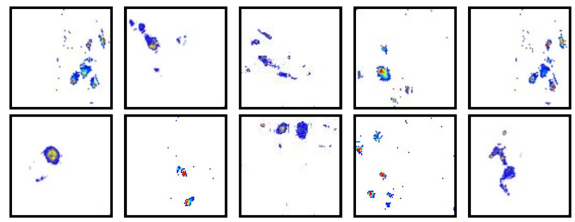
## 2. Feature extraction

The problem of feature extraction from pressure data can be viewed as a pattern description problem that can be tackled using classical approaches from the literature. Some requirements should be specified for the feature extraction task in order to properly achieve the posture classification. The main requirement is that the features should be translation and rotation invariant. Scale invariance is also a desirable property but we did not consider it as a requirement in this work and we are planning to work on that in future work. The translation invariance property can be easily achieved by considering the center of gravity as a reference point. For the rotation invariance, extensive works are described in the literature. Hu [8] and Zernike moments [9] outline classical methods to design rotation invariant features. A simple approach based on the selection of geometric measures that are rotation invariant, e.g., perimeter, eccentricity, solidity, Euler number, area, convex area, major and minor axis lengths [10] is also an alternative for obtaining rotation invariant features. In our experiments, however, these approaches showed a limited robustness against the high variation of the pressure patterns for a single posture as depicted in Figure 1. The reason of such large intra-class variability is the high deformability of the human body due to articulations and the occlusion of body parts.

### 2.1 Dartboard features

We considered a polar, order-invariant representation with the gravity center of the pressure pattern as a reference. The polar domain was divided into cells (intersection areas of rings and sectors) as illustrated in Figure 2. The pressure sum per cell was computed and subsequently higher-order statistics of these summed pressure values across cells were acquired for each ring. These statistics were the mean, standard deviation, kurtosis and skewness. The feature vector was obtained as a concatenation of the statistics from all rings in a single pressure frame. In a first approach the width of all rings has been set to be equal. This setting led to cells, on a larger radius, with an increasing surface. Therefore feature components obtained from cells that were far from the center had more weight than the others. To correct this, cell areas $A_k$ were made constant by varying the rings' radius $R_k$ as follows

$$R_k = \sqrt{k+1}\,R_0,\ A_k = \frac{1}{2}\theta R_0^2.$$



$P_1$ $P_2$ $P_3$ $P_5$ $P_6$

**Figure 1 – First row: Intra-class pressure frame samples from posture $P_4$: lying on belly. Second row: inter-class samples from postures $P_i$ resp. sitting, standing, lying on back, crawling and lying on side.**

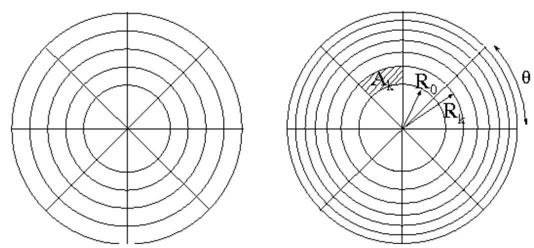



**Figure 2 – polar grid with constant (left) and non-constant ring widths (right).**

## 3. Posture classification

The dartboard features were first extracted and then the classifier was trained using a training dataset. The posture classification was therefore viewed as a general classification problem where classical classifier can be used. A majority vote fusion of the following classifiers was applied: linear, quadratic, SVM and k-NN. Since the classifiers were trained on single pressure frames without incorporating temporal information, the classification of unseen data would also provide posture classes of individual frames. However the temporal information can be valuable to improve the results knowing that a baby posture does not quickly change over time.

A simple temporal classifier was used. First, single frames were classified then a sliding time window was selected around the frame of interest. The dominant posture classes were determined from this window as follows: If the ratio between the size of the first and second class modes was above a certain threshold then the temporal posture classification was taken as of the dominant class. Otherwise the single-frame classification was kept. The threshold allowed tuning the confidence in the dominant class.

## 3. Experiments

The experiments were carried out with data obtained from a one-year-old baby. The recordings of pressure data were acquired at 3 different dates. The first recording ($S_1$) was acquired at an age of 14 months, the second ($S_2$) at 16 months and the last recording ($S_3$) at 19 months. During the recordings, the child could freely move and play at the mat without intervention. The pressure recordings were accompanied by synchronous video recordings to facilitate manual labeling of individual frames. In total, 30 minutes of annotated pressure data were obtained.

**Table 1. Number of frames per posture $P_i$ for the different datasets.**

| | $P_1$ | $P_2$ | $P_3$ | $P_4$ | $P_5$ | $P_6$ | $P_7$ | Total |
|---|---|---|---|---|---|---|---|---|
| $S_1$ | 1579 | 642 | 214 | 157 | 1067 | 50 | 139 | 3848 |
| $S_2$ | 1511 | 959 | 95 | 428 | 5637 | 388 | 47 | 9065 |
| $S_3$ | 530 | 2172 | 328 | 812 | 4468 | 301 | 64 | 8675 |

Frames from the 3 recordings were annotated manually based on seven classes: sitting, standing, lying on the back, lying on the belly, lying on the side and a noise class we called other. This class consisted of samples that could not be classified as one of the other 6 postures. For an overview refer to Figure 1 and Table 1.

The proposed dartboard features were benchmarked w.r.t. the chosen state of the art features namely Hu, Zernike moments and geometric features. In order to have a good overview on the performance we considered all combinations of the 3 datasets in training and testing. In Table 2, the rows indicate the datasets used for training and the column indicates the dataset used for testing.

In a first experiment the temporal information was discarded i.e. no time stamp was used and therefore only single pressure data frames were used. Each dataset was split in training and testing datasets. Typically one third was used for training and two third for testing. This operation was repeated on all possible combination to obtain a variance estimation of the classification error. A number of classifiers have been tested namely linear, quadratic, k-NN and SVM classifiers. A majority vote fusion scheme of the previous classifiers was applied. A separate initial test was performed to manually tune settings such as SVM parameters (kernel parameter and margin parameter) and k-NN parameters. The original pressure data frame had a size of 84x96. A bi-linear interpolation of the raw data of factor of 4 leading to a size of 336x384 allowed a significant performance improvement of 5% to 7% in terms of classification error. Therefore this interpolation step was used as default pre-processing step for all the following results.

Table 2 provides a benchmark of the different tested feature sets. It shows that the performances of the state of the art features were poor in general. A possible explanation is that features based on moments are not suited when high distortions of the patterns are present. The geometric features provided only rough description of the pressure pattern which seems to be not enough to discriminate between the different posture classes. The proposed dartboard features accomplish a good trade-off between invariance properties and robustness to distortion and occlusion. The quantization of the pressure patterns obtained by the usage of dartboard representation, as shown in Figure 2, ensures the required properties. We observe also that the train/test combination ($S_i$,$S_i$), that are on the diagonals of Table 2, are better than for a combination of ($S_i$,$S_j$) $i \neq j$. This is due to the high correlation between train and test set since they are both from the same dataset $S_i$.

**Table 2. Classif. Error (%) for (a) Hu, (b) Zernike moments, (c) Geometric features and (d) Dartboard features.**

| **(a)** | $S_1$ | $S_2$ | $S_3$ |
|---|---|---|---|
| $S_1$ | 24±4.0 | 29.3±1.5 | 46.2±2.3 |
| $S_2$ | 42.6±1.4 | 15.9±1.0 | 42±0.6 |
| $S_3$ | 60.2±1.8 | 31.8±2.5 | 19.7±1.0 |

| **(b)** | $S_1$ | $S_2$ | $S_3$ |
|---|---|---|---|
| $S_1$ | 14.3±0.6 | 83.5±0.7 | 88.5±4.0 |
| $S_2$ | 68.4±3.5 | 12.2±0.67 | 75.2±2.6 |
| $S_3$ | 86.2±1.1 | 74.8±2.2 | 7.78±0.4 |

| **(c)** | $S_1$ | $S_2$ | $S_3$ |
|---|---|---|---|
| $S_1$ | 15.2±0.5 | 52.8±0.9 | 63.9±2.2 |
| $S_2$ | 59.5±2.5 | 10.2±0.40 | 47.7±8.8 |
| $S_3$ | 66.5±1.6 | 37.8±0.05 | 17.1±0.9 |

| **(d)** | $S_1$ | $S_2$ | $S_3$ |
|---|---|---|---|
| $S_1$ | 1.82±0.3 | 11.7±0.6 | 14.8±0.7 |
| $S_2$ | 21.8±1.8 | 1.7±0.2 | 18.7±1.2 |

| | | | |
|---|---|---|---|
| $S_3$ | 30.2±2.2 | 19.2±1.4 | 1.74±0.3 |

The non-uniform dartboard grid ensured that all feature components were extracted with a uniform area. Table 3 shows classification errors obtained with the non-uniform dartboard grid. This result should be compared with Table 2-d. In most of the training/testing dataset combinations the classification performance has improved. On average an improvement of around 10% is obtained.

**Table 3. Classif. error (%) using Dartboard features with non-constant ring widths.**

| | $S_1$ | $S_2$ | $S_3$ |
|---|---|---|---|
| $S_1$ | **1.65±0.3** | 12.2±2.2 | **13.4±0.7** |
| $S_2$ | **19.5±2.4** | 1.92±0.1 | **11.6±1.3** |
| $S_3$ | 34.2±4.0 | **9.71±0.7** | 1.77±0.2 |

All results of the experiments presented above had been carried without considering the temporal information (or voting across frames). Table 4 shows an overview of classification error rates when a temporal voting scheme, described in Section 3, is used. A significant improvement of about 10% is obtained when a window of 200 frames is used.

**Table 4. Classif. Error (%) using Dartboard features and temporal voting.**

| | $S_1$ | $S_2$ | $S_3$ |
|---|---|---|---|
| $S_1$ | 0.64±0.1 | 9.77±3.1 | 13.07±1.6 |
| $S_2$ | 17.37±2.3 | 1.28±0.2 | 11.10±0.6 |
| $S_3$ | 21.66±4.1 | 6.58±1.8 | 1.53±0.2 |

Table 5 shows an example of the confusion matrix obtained with the proposed feature and the voting scheme classifier. The majority of errors occurs for the belly, back and side postures. This can be explained by the high similarity of to the two postures.

**Table 5. Example of confusion matrix. Rows indicate the real postures and columns the estimated ones.**

| | $P_1$ | $P_2$ | $P_3$ | $P_4$ | $P_5$ | $P_6$ | $P_7$ |
|---|---|---|---|---|---|---|---|
| $P_1$ | 1489 | 5 | 0 | 5 | 1 | 11 | 0 |
| $P_2$ | 13 | 892 | 38 | 0 | 6 | 3 | 7 |
| $P_3$ | 10 | 10 | 51 | 8 | 6 | 10 | 0 |
| $P_4$ | 11 | 0 | 6 | 330 | 81 | 0 | 0 |
| $P_5$ | 38 | 167 | 5 | 126 | 4958 | 244 | 99 |
| $P_6$ | 1 | 43 | 44 | 20 | 146 | 131 | 3 |
| $P_7$ | 0 | 45 | 0 | 0 | 0 | 0 | 2 |

# 4. Conclusions

In this paper we have considered the problem of baby-posture classification from pressure data. We formulated the posture classification as a problem of the feature design from the pressure patterns in combination with generic machine learning classifiers. The features should be rotation and translation invariant and robust to certain extends against deformation. The proposed dartboard features provided good results with average error rates of about 12%. The incorporation of temporal information allowed an improvement of the performance to 9% classification error. As future work, we are interested in a better modeling of dynamic postures such as walking, crawling and the transition between postures in order to improve the classification performance. This could be achieved by discarding unlikely transitions such lying on the belly and sitting which normally requires intermediate postures such as crawling. Furthermore, evaluation on more extensive data sets is required to investigate the effect of age of children.

# References


[1] L. Berk. *Child Development.* Allyn & Bacon, 2008.

[2] N. Yildirim, Fitzpatrick MF, Whyte KF, Jalleh R. The effect of posture on upper airway dimensions in normal subjects and in patients with the sleep apnea/hypopnea syndrome. *American Review of Respiratory Disease*, 1991.

[3] H. Hibi, M. Ueda. Body posture during sleep and disc displacement. *Journal of Oral Rehabilitation,* 2005.

[4] Kamiya, K. et al., Sitting posture analysis by pressure sensors, 2008, *ICPR* .

[5] Hasia, C.C. et al., Analysis and comparison of sleeping posture classification methods using pressure sensitive bed system.2009, *EMBC.*

[6] T. Harada, A. Saito, T. Sato and T. Mor. Infant Behavior Recognition System Based on Pressure Distribution Image. *IEEE ICRA.* 2000.

[7] G. Weinberg, R. Fletcher, S. Gan. The baby sense environment: enriching and monitoring infants' experiences and communication. *Conference on Human Factors in Computing Systems.* 1998.

[8] Hu, M. Visual pattern recognition by moment invariants. *IEEE Trans. on Information Theory.* 1962.

[9] A. Khotanzad, Y. Hong. Invariant image recognition by Zernike moments. 1990, *IEEE Transactions on PAMI.*

[10] Jain, A. *Fundamentals of digital image processing.* Prentice Hall, 1989.