Gait Recognition with Kinect

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ABSTRACT

The prominence of systems for automatic person identification has risen increasingly during the past years. One biometric technique for unintrusive identification is gait recognition which offers the possibility to recognize and identify movement patterns of persons from some distance away. In former work, gait recognition is mainly achieved with camera systems. In this paper, we present an approach for gait recognition based on Microsoft Kinect, a peripheral for the gaming console XBOX 360, with an integrated depth sensor alowing for skeleton detection and tracking in realtime. We evaluate a number of body features together with steplength and speed, their relevance for person identification, and present the results of an empirical evaluation of our system, where we were able to accomplish a success rate of more than 90% with nine test persons.

Categories and Subject Descriptors

I.5.2 [**Pattern Recognition**]: Design Methodology—*Classifier design and evaluation, feature evaluation and selection*

Keywords

Kinect, gait recognition

1. INTRODUCTION

Systems facilitating robust, automatic identification of persons have gained increasing acceptance during the recent years [19]. Systems for automatic identification play a decisive role in surveillance scenarios (e.g., monitoring high security areas like banks or airports). Biometric techniques use characteristic physiological and behavioral specifics of different persons for identification. Examples for such techniques are the recognition of iris, face, fingerprint, gait, or the handwriting. *Gait recognition* is a relatively new (according to Jain et al. [8] actually the most recent) biometric technique. Using gait as a biometric gained increasing attention during the past years, since it offers many advantages compared to other biometrics [21, 10, 19, 4]. Considering marker-free systems, (i.e., no sensors or other devices are placed on the subject being identified), gait recognition is an unintrusive technique, meaning that no physical contact between subject and measurement device is necessary. In marker-free gait recognition, person identification is usually executed by analyzing video sequence recordings. Allowing for marker-free person identification is one of the key advantages of using gait as a biometric [19]. In contrast to systems using for example the iris or the fingerprint of a person as biometrics, identification by gait does neither require the cooperation nor the attention of the subject. These properties are particularly important in the aforementioned surveillance scenarios where subject cooperation can not be expected and the subject's awareness is possibly not desired at all. Another advantage of this biometric technique is the fact that identification can be performed on a distance and that gait is hard to hide or to imitate.

Microsoft Kinect is a peripheral for the XBox 360 gaming console, enabling players to control games with body motion and gestures without additional input devices. To this end Kinect enables skeleton-detection and -tracking of people in realtime by an integrated depth camera. Using an SDK provided by Microsoft, the Kinect sensor can be connected with a personal computer and its datastreams can then be used in own applications.

Existing gait recognition approaches mostly use standard video cameras for capturing and recording the movement of walking persons. Here, the main difficulty lies in the extraction of characteristic features for identification. The challenges of existing gait recognition approaches and the possibilities Kinect offers lead to the assumption that the problem of gait recognition could be simplified using the Kinect sensor. Using a prototypic implementation of a gait recognition system, we evaluate the possibilities of gait recognition using Kinect. Using a simple set of features and testing three different classifiers, we observed promising results concerning person recognition, especially when using a Naive Bayes classifier.

The paper is structured as follows: In Section 2, we give a short overview over related work. We then introduce our Kinect based gait recognition approach in Section 3. In Section 4, we present the results we achieve with the prototypical gait recognition system. Section 5 concludes this paper with a discussion of our results and possible improvements in future work.

2. RELATED WORK

Gait recognition research was motivated by the early psycho-physiological studies of Johansson [2]. Using *moving light displays* (MLD), light points attached to the body, Johansson showed that people are able to recognize human motion solely by the movement of the MLDs [9]. The biomechanic studies of Perry et al. [16], Murray [12] and Winter [22] led to the assumption that gait is a characteristic and possibly individual trait of a person.

Gait recognition is a pattern recognition problem. Most of the existing gait recognition approaches rely on an analysis of the binary silhouette of walking persons for identification [11, 13]. Existing approaches can be divided into *model-based* and *model-free* approaches. Model-based approaches try to model the human body and its motion. An often used model is the *stick-figure model* where the human body is represented by sticks and joints [14]. The model is fitted to every image of the walking sequence and its parameters (angle velocities, trajectories of joints, limb lengths) are used as features for classification. Therefore, model-based approaches are basically viewpoint and scale invariant [21]. The drawbacks of the model-based approach are the difficulties in model construction, model fitting and parameter extraction. Model fitting, e.g., finding extremities and joints in (often low-quality) video sequences, is particularly challenging since the subsequent parameter calculations often require high computational efforts [20, 11, 19, 21].

According to Liu et al. [10] the first gait recognition approach was developed by Nyogi und Adelson [15]: The outline of the subject is used to control a simple stick-figure model. The angles of thighs and lower legs are extracted and used as feature for classification with a Nearest Neighbor algorithm. Bobick und Johnson [3] also present a model-based approach. Using simple activity-specific parameters (height, torso length, leg length and step length) measured in the *double-support phase*[1] of the gait cycle, they achieve promising results. BenAbdelkader et al. [1] present a similar approach, but also use dynamic features such as the change in apparent height of the subject and its step frequency, achieving better results than Bobick and Johnson. In model-free approaches gait is characterized by the spatio-temporal patterns generated by the (binary) silhouette of the walking persons [1]. Here, gait is solely characterized by the appearance and movement of the silhouette. The advantage of model-free approaches over model-based approaches is their often easier implementation and lesser computational complexity [19, 21]. Despite their conceptual simplicity, model-free approaches are able to achieve solid recognition rates and are therefore prevalent in literature. The major drawback of these approaches is their susceptibility to any changes of the silhouette, e.g. by clothing, carrying of objects and occlusions. Phillips et al. [17, 18] present a model-free approach where they extract bonary silhouettes from the walking subject which are then scaled to a uniform size. Classification is then achieved by a image comparison between database- and test-silhouettes.

[1]the phase of the gait cycle where both feet are maximally apart

3. SKELETON-BASED GAIT RECOGNITION WITH KINECT

We propose a model-based approach for gait recognition based on the skeleton provided by Mircosoft Kinect. As said before, Kinect provides a high quality skeletal model of up to two users in front of the Kinect sensor in a Cartesian coordinate system. We decided to use this skeletal data for recognition and did not use the depth- and color-images directly.

Our system consists of three components: The first component records the skeletal information offered by Kinect which is then processed by the second component for feature extraction. Finally, we use the machine learning framework WEKA [5] to identify a person on the basis of previously recorded training data (see Figure 1).

3.1 Features

The Kinect SDK offers the detection and tracking of 20 different skeletal points, from head over hips to the feet. Using these points, we define thirteen biometric features for the identification of a person: The height, the length of legs, torso, both lower legs, both thighs, both upper arms, both forearms, the steplength, and the speed. While the first eleven features are static, i.e., cannot be changed on purpose, the last two features may depend on the situation. Nevertheless, when unaware of identification attempts, these features may be an additional characteristic for a human being. The features are evaluated with respect to relevance for classification in Section 4 and are to some extent independent of clothing. Using those high-level features, our approach is similar to those of Bobick und Johnson [3] and BenAbdelkader et al. [1].

3.2 Classifiers

We evaluate the performance of our choice of features with the help of three different classifiers: 1R, a C4.5 decision tree and a Naive Bayes classifier.

1R generates a classification rule based upon a single feature in the training data. All patterns in the training data are then classified by the value of this feature. Despite its simplicity, 1R often yields good results in diverse scenarios, as evaluated in [7]. We use the 1R classifier to evaluate the general difficulty of our classification task.

The C4.5 algorithm in general generates a decision tree in which inner nodes represent binary tests on a feature value and leaf nodes represent classes. Classification of a new instance is done by following the path along the tree as it is given by the feature values and assigning the class of the leaf node finally reached. In every step of the tree generation, the feature yielding the highest *information gain* is selected as a test feature which essentially means, that the algorithm tries to find a test such that the resulting classification tasks along both branches is as simple as possible [6]. A decision tree can generally be used to find some ordering of importance of features, as important features are typically used early inside a tree generated using the information gain criterion.

The Naive Bayes classifier is a probabilistic classifier based on the Bayes' law. It is called *naive* because it assumes that the features are statistically independent, meaning that the values of one feature are not affected by the values of other

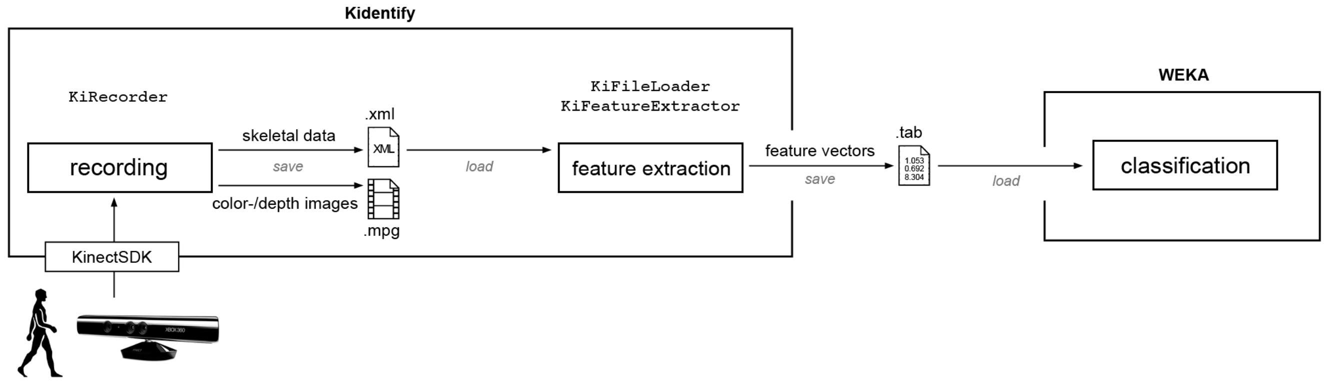

Figure 1: schematic of our prototypic gait implementation

features. Though this independence assumption is obviously violated in gait recognition, the Naive Bayes classifier can still yield good results in practice.

4. EXPERIMENTAL EVALUATION

Before describing the experiment and our results in detail, we present the results of a short field study of Kinect's accuracy concerning the chosen static features in an ideal setting. For this experiment, we recoded 20 short video sequences of a person standing still and facing the Kinect. The standard deviation for the description of each feature was less than 2cm which we consider sufficiently accurate for gait recognition.

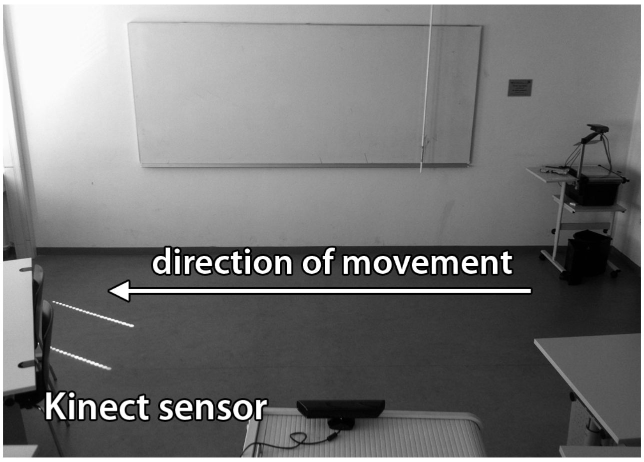

Figure 2: Experimental setup

To evaluate the relevance of each feature for the identification task, we carried out the following experiment: nine persons had to walk from right to left in front of the Kinect sensor as depicted in Figure 2. They were told to walk in their common gait at their normal speed. Each person walked through the field of view, while the Kinect recorded a sequence of frames capturing his side view. For each person, the experiment was carried out eight times. Unfortunately, the Kinect skeleton recognition was only successful for eight testusers. For one person the Kinect was only able to recognize a skeleton in three out of the eight testruns. Thus, the experiment yielded 67 labeled feature vectors, which were used for training and testing of the classifiers. Note that the standard deviation of the length of each static feature was with less than 3cm comparable to the ideal setting. The standard deviation of steplength was 5cm and was 7cm concerning the speed.

Using all features in a 7-fold cross-validation led already to quite good classification results: 1R chose the feature average height for his single test and was already able to obtain a success rate of 62.7%. C4.5 yielded a 76.1% success rate, while Naive Bayes had the best success rate with 85.1%. However, C4.5 did not include all features, but ignored the dynamic features as well as all limbs except the left upper arm. So a set F_4 of the four features height, length of legs, length of torso, and length of the left upper arm were sufficient to create a decision tree for the full classification of our testset. When utilizing Naive Bayes solely with these features, a success rate of 91.0% could be achieved.

Finally, we trained the classifiers with two other sets of features. The first set F_7 contains all static features which are not in F_4, while the second set F_d consists of only the dynamic features steplength and speed. With F_7, Bayes yielded 81.1% success rate, with F_d 55.2%, which is promisingly better than randomness indicating that these features are valuable though they have been ruled out by the other features. Still, a system which can measure these features has a good chance of being able to correctly distinguish between people. All success rates (including those of the other classifiers for F_7 and F_d) are depicted in Table 1.

Classifier	All Features	F_4	F_7	F_d
1R	62.7%	62.7%	43.3%	25.4%
C4.5	76.1%	76.1%	68.7%	55.2%
Naive Bayes	85.1%	91.0%	81.1%	55.2%

Table 1: Success rate of classifiers based on different feature sets using 7-fold cross-validation

These results show the feasibility of person identification based on gait recognition with Kinect. Furthermore, we can deduce some recommendations for gait recognition based on limbs, speed and steplength: Even if the length of various limbs is closely connected with each other, the proportions might vary for different persons. This can be deduced by the fact that there is a gain in the success rate from 1R to C4.5 and an even larger gain for Naive Bayes although the latter assumes an independence of all features. For a small set of persons, our proposed features seem to be sufficient for identification, however, the approach is not suitable for identification of individuals among crowds, since the length of multiple limbs would have to be extracted correctly.

5. CONCLUSION AND FUTURE WORK

In this paper, we presented a model based approach to gait recognition based on Microsoft Kinect. We use 13 biometric features such as the height, the length of limbs, and the steplength which are computed from the skeleton frames generated by Kinect. Based on testdata from 9 different persons, the three basic classifiers Naive Bayes, 1R, and C4.5 were trained and evaluated concerning the success rate of their classification. Based on the features used of the decision tree C4.5, we found out that only four features, namely height, length of legs, length of torso, and length of the left upper arm, were sufficient to correctly identify a person in 91% of all cases using the complete video from the specific experiment and the Naive Bayes classifier. Classification based solely on steplength and speed still yielded 55.2% success rate using either Naive Bayes or the decision tree.

We believe that our results from gait recognition with Kinect are promising and show that reliable discrimination of individuals in a small set of persons is possible. However, a larger experimental setup should provide more insight into the variations of body parameters. Especially in application scenarios with large numbers of people, tracking and classifying the trajectory of certain limbs such as hand and feet could add to the accuracy of the system. Moreover, a combination with other identification systems such as facial recognition could add to the dependability of such a system.

6. REFERENCES

[1] C. BenAbdelkader, R. Cutler, and L. Davis. View-invariant estimation of height and stride for gait recognition. *Biometric Authentication*, pages 155–167, 2006.

[2] C. BenAbdelkader, R. Cutler, and H. Nanda. Eigengait: Motion-based recognition of people using image self-similarity. *Audio-and Video-Based*, pages 284– 294, 2001.

[3] A. F. Bobick and A. Y. Johnson. Gait recognition using static, activity-specific parameters. *Proceedings of the 2001 IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, pages 423–430, 2001.

[4] D. Cunado, J. Nash, M. Nixon, and J. Carter. Gait extraction and description by evidence-gathering. In *Proc. of the International Conference on Audio and Video Based Biometric Person Authentication*, volume 48, pages 1–6, 1995.

[5] M. Hall, E. Frank, G. Holmes, B. Pfahringer, P. Reutemann, and I. H. Witten. The weka data mining software: An update. *SIGKDD Explorations*, 11, 2009.

[6] J. Han and M. Kamber. *Data mining: concepts and techniques.* Morgan Kaufmann Pub, 2001.

[7] R. Holte. Very simple classification rules perform well on most commonly used datasets. *Machine learning*, (1988):63–91, 1993.

[8] A. K. Jain, R. Bolle, and S. Pankanti. *Biometrics: personal identification in networked society.* Kluwer Academic Publishers, 1999.

[9] G. Johansson. Visual perception of biological motion and a model for its analysis. *Attention, Perception, & Psychophysics*, 14(2):201–211, 1973.

[10] L. Liu, W. Jia, and Y. Zhu. Survey of gait recognition. *Emerging Intelligent Computing Technology and Applications. With Aspects of Artificial Intelligence*, pages 652–659, 2009.

[11] Z. Liu and S. Sarkar. Effect of silhouette quality on hard problems in Gait recognition. *IEEE transactions on systems, man, and cybernetics. Part B, Cybernetics : a publication of the IEEE Systems, Man, and Cybernetics Society*, 35(2):170–83, Apr. 2005.

[12] M. P. Murray. Gait as a total pattern of movement. *American Journal of Physical Medicine*, 46(1):290, 1967.

[13] M. Nixon. New Advances in Automatic Gait Recognition. *Information Security Technical Report*, 7(4):23–35, Dec. 2002.

[14] M. Nixon, J. Carter, D. Cunado, P. Huang, and S. Stevenage. Automatic gait recognition. *Biometrics*, 31(5):231–249, Jan. 2002.

[15] S. Niyogi and E. Adelson. Analyzing and Recognizing Walking Figures in XYT. In *Proceedings of the Conference on Computer Vision and Pattern Recognition*, pages 469–474, 1994.

[16] J. Perry and Others. Gait analysis: normal and pathological function. *Journal of Pediatric Orthopaedics*, 12(6):815, 1992.

[17] P. Phillips, S. Sarkar, I. Robledo, P. Grother, and K. Bowyer. Baseline results for the challenge problem of HumanID using gait analysis. In *Proceedings of Fifth IEEE International Conference on Automatic Face Gesture Recognition*, pages 137–142, 2002.

[18] P. Phillips, S. Sarkar, I. Robledo, P. Grother, and K. Bowyer. The gait identification challenge problem: data sets and baseline algorithm. In *Proceedings of 16th International Conference on Pattern Recognition*, pages 385–388, 2002.

[19] F. Tafazzoli and R. Safabakhsh. Model-based human gait recognition using leg and arm movements. *Engineering Applications of Artificial Intelligence*, 23(8):1237–1246, Dec. 2010.

[20] R. Urtasun and P. Fua. 3d tracking for gait characterization and recognition. *Automatic Face and Gesture Recognition,*, pages 17–22, 2004.

[21] J. Wang, M. She, S. Nahavandi, and A. Kouzani. A Review of Vision-Based Gait Recognition Methods for Human Identification. *2010 International Conference on Digital Image Computing: Techniques and Applications*, pages 320–327, Dec. 2010.

[22] D. A. Winter. Biomechanics and motor control of human gait: normal, elderly and pathological. 1991.