LNAI 10564

Serafín Moral · Olivier Pivert
Daniel Sánchez · Nicolás Marín (Eds.)

Scalable Uncertainty Management

11th International Conference, SUM 2017
Granada, Spain, October 4–6, 2017
Proceedings

Springer

Editors
Serafín Moral
University of Granada
Granada
Spain

Daniel Sánchez
University of Granada
Granada
Spain

Olivier Pivert
University of Rennes I
Lannion
France

Nicolás Marín
University of Granada
Granada
Spain

ISSN 0302-9743 ISSN 1611-3349 (electronic)
Lecture Notes in Artificial Intelligence
ISBN 978-3-319-67581-7 ISBN 978-3-319-67582-4 (eBook)
DOI 10.1007/978-3-319-67582-4

Library of Congress Control Number: 2017953397

LNCS Sublibrary: SL7 – Artificial Intelligence

Printed on acid-free paper

This Springer imprint is published by Springer Nature
The registered company is Springer International Publishing AG
The registered company address is: Gewerbestrasse 11, 6330 Cham, Switzerland

Contents

Short Papers

A Fuzzy Ontology-Based System for Gait Recognition Using Kinect Sensor

Fernando Bobillo[1(✉)], Lacramioara Dranca[2], and Jorge Bernad[1]

[1] Aragon Institute of Engineering Research (I3A), University of Zaragoza, Zaragoza, Spain
{fbobillo,jbernad}@unizar.es

[2] Defense University Center (CUD), General Military Academy, Zaragoza, Spain
licri@unizar.es

Abstract. Gait recognition involves the automatic classification of human people from sequences of data about their movement patterns. This paper describes our ongoing work in the development of a gait recognition system using Microsoft Kinect data and based on fuzzy ontologies to manage the imprecision of the data and to improve the system scalability.

Keywords: Gait recognition · Fuzzy ontologies · Kinect sensor

1 Introduction

The problem of gait recognition consists of automatically classifying human people by analyzing data about their movement patterns. Gait recognition has many applications, including security (e.g. authentication and surveillance) and medicine (e.g. automatic support for the diagnosis of neurological diseases). Furthermore, it has several advantages with respect to other biometrical measures for human recognition. For example, it is non-intrusive, does not require any collaboration from the subject, and involves less confidential data than other techniques, such as face recognition.

In the last years we have witnessed an increase in the number of low cost sensors to capture pose sequences to compute biometrical measures related to the human gait. An example is Microsoft Kinect, a motion sensing input device originally conceived as a peripheral for video game consoles.

Although there is a notable effort in the gait recognition using Microsoft Kinect (see Sect. 2 for a discussion), existing approaches generate big amounts of data which are difficult to understand by a non-expert or to reuse between different applications. For this reason, we advocate for the combination of Semantic Web technologies to represent human Microsoft Kinect data and the biometrical features for human gait motion analysis computed using them. Due to the intrinsic imprecision of the original data, we propose to use fuzzy ontologies to use fuzzy sets rather than precise crisp values at production stage.

This paper describes our ongoing work. The main objectives of our research and the main contributions so far can be summarized as follows:

S. Moral et al. (Eds.): SUM 2017, LNAI 10564, pp. 397–404, 2017.
DOI: 10.1007/978-3-319-67582-4_29

- Our system uses fuzzy ontologies to represent Microsoft Kinect data and biometrical features for human gait motion analysis.
- Our data segmentation is based on steps rather than on full sequences.
- We reduce the number of variables with respect to previous works.
- At production stage, data corresponding to a new recording can be compared only with a customizable number of candidates from our database.
- We plan to provide a public database with data obtained using Kinect V2.

The remainder is organized as follows. Section 2 overviews some related work. Then, Sect. 3 details the architecture of our system and summarizes some preliminary results. Section 4 ends with conclusions and ideas for future research.

2 Related Work

This section summarizes most of the previous work on gait recognition using the Kinect sensor or on the use of ontologies to represent Kinect data.

Gait recognition and Kinect. After the commercial launch of Kinect in 2011, several research papers have approached the gait analysis for human recognition. One of the first approaches is [9], where the authors observed promising results concerning person recognition using a Naive Bayes classifier and a simple set of features obtained from nine people with a Kinect sensor. A real time approach for Kinect based recognition is presented in [6]. In that case the features are characterized as static (height, length of bones) or dynamic (angles of joints). Several distances where used between these features and finally a nearest neighbor classifier obtained around 80% accuracy for ten people. In [8] a framework for gait-based recognition is proposed, based on a publicly available Kinect dataset with 30 people. The authors extract 16 dimensional vectors from the dataset and use several dissimilarity tests and achieve 93.29% identification rate and 99.11% gender recognition rate. Some steps further are taken in [7] with a new method for fusing information from Riemannian and Euclidean features representation that achieves 95.67% accuracy. Moreover, the authors mention a new dataset for gait recognition captured from 30 people using the more recent Kinect V2 but, unfortunately, it is not currently publicly available.

Ontologies and Kinect. There have also been some previous approaches to represent Kinect-related data using classical ontologies [4] and fuzzy ones [3]. The authors even developed the so-called *Kinect ontology*. However, despite this generic name, their approach is strongly focused on a different application, recognition of human activity, and cannot be reused in our scenario. For example, *Kinect ontology* was not designed to encode directly the information directly obtained from the sensors, and its fuzzy extension does not discuss a fuzzy representation of the relevant features for gait recognition.

3 Architecture of the System

The proposed system has four main components: a data capture phase, a preprocessing phase, an ontology and a decision phase, as shown in Fig. 1.

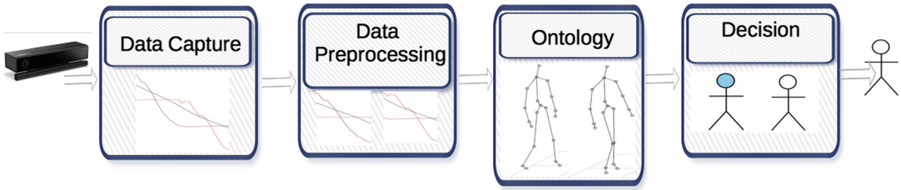

Fig. 1. Architecture of the system

Data Capture. The Data Capture module interacts directly with the sensor and collects raw data from a Kinect sensor. The Kinect sensor actually integrates several sensors (e.g., RGB camera, depth sensor, or infrared sensor) from which several joint points of the human skeleton are obtained. These joint points are retrieved as points in a 3D-space where the coordinate origin is located at the center of the Kinect sensor. As an example, Fig. 1(Data Capture) shows both the feet and the spine base values in the depth axis (z-axis) of a person walking two steps. Due to inaccuracy of the sensor, the coordinates for each joint point are not precise, so it is needed to prune the data that can be incorrectly taken by the sensor. The module explained in the next section is entrusted of such task. This inaccuracy will be also managed by the fuzzy ontology.

Data Preprocessing. Next, the data captured in the previous phase are preprocessed. The data preprocessing module contains several algorithms for steps segmentation, noise reduction, and feature extraction.

Our system uses a step-based identification approach rather than using entire sequences. Sequence means in this context a Kinect register of a person walking towards the camera. Usually, sequences contain 3–4 steps. In order to detect the steps in a sequence, a strategy based on local maximums of the distance between the feet time series is used. For training purpose we used the *UPCVGait* dataset [8], a publicly available dataset acquired using Kinect V1. Figure 1(Data Preprocessing) shows an example of the segmentation done for a person walking two steps (both feet and the spine base data are shown). Some strategies based on length of the bones, height of a person, and variation of the movement direction in a step have been used for noise reduction purposes.

Then, the feature extraction is performed for each of the steps identified previously. We identified three kind of features:

- *Anthropological features:* height, humerus length, forearm length, thigh length and shin length. As these measures may slightly vary from frame to frame, we compute mean, max, min, and standard deviation for each detected step.

– *Step related features:* step length, step width. Since the walking direction of a person may vary and is not always straight to the location of the camera, an angular rotation over the y-axis (vertical axis) has been applied firstly in order to align the direction of walking of each person with the position of the Kinect sensor.
– *Angle related features:* angles of the projections on the xz and yz plane of each of the previously mentioned bones, both left and right ones. Inspired by [8] and before computing these angles, a new angular rotation has been applied in order to align the vertical axis with the inclination of the torso (the line connecting the center of the hips with the center of the shoulders) of each person. As these angles are different from frame to frame, mean, max, min and standard deviation values are computed for each step.

We have used WEKA (namely the WrapperSubsetEval method, that evaluates attribute sets by using a learning scheme) to obtain a selection of the most representative attributes, which in our case were 12 [10]. This way, our system uses a smaller number of attributes than previous works.

Fuzzy Ontology for Gait Recognition. The benefits of using a fuzzy ontology are two-fold: firstly, data representation is more appropriate for human understanding and machine reuse; secondly, we can provide a reduced number of candidates to the Decision Module.

Our fuzzy ontology is able to represent raw Kinect data about the movement of a person but also biometric features computed from them. Fuzzy ontologies extend classical ontologies with ideas of fuzzy logic [11]. While in classical set theory elements either belong to a set or not, in fuzzy set theory elements can belong to some degree, usually ranging in $[0, 1]$. As in the classical case, 0 means no-membership and 1 full membership, but now a value between 0 and 1 represents the extent to which x can be considered as an element of the fuzzy set. When applying these ideas to fuzzy ontologies, it is possible to define fuzzy extensions of the concepts, properties, axioms, and datatypes. In our case, our fuzzy ontology includes *fuzzy datatypes*, replacing crisp values with a more general fuzzy membership function. For example, assume that we want to recognize an individual human001 using some biometrical metrics, such as its maximal height. Rather than representing that the value of the data property maxHeight for human001 is 190 cm, we can take into account the imprecision of the sensor by considering instead a triangular function (see Fig. 2(a)) such that $\pm d$ cm is considered as acceptable. While one could consider using a better sensor, we aim at using low cost devices and thus must deal with such imprecision.

Our ontology has been developed using Protégé [5] ontology editor. Classes, properties, individuals, and most of the axioms are represented as usual. To represent the fuzzy datatypes, we have used Protégé plug-in called *Fuzzy OWL 2* that can be used to create and edit fuzzy ontologies [1]. The idea is to use a classical OWL 2 ontology with OWL 2 annotations to add the fuzzy information that OWL 2 cannot directly encode, the plug-in makes the annotations syntax transparent to the users.

As discussed in Sect. 2, we needed to develop it from scratch. To represent the Kinect data, we consider 4 mutually disjoint classes. For each instance of Human, there are several recordings. Every video obtained using Kinect is represented as an instance of Sequence and each sequence is composed of several instances of Frame. After some preprocessing, we can also divide a sequence in several instance of Step, so that each step is related to a unique sequence. Each step contains several frames, but each frame is associated at most to one step (if the human stops walking at some point of the video, there might be frames not associated to any step). We also have object and data properties with their corresponding some domain, range, and functionality restrictions.

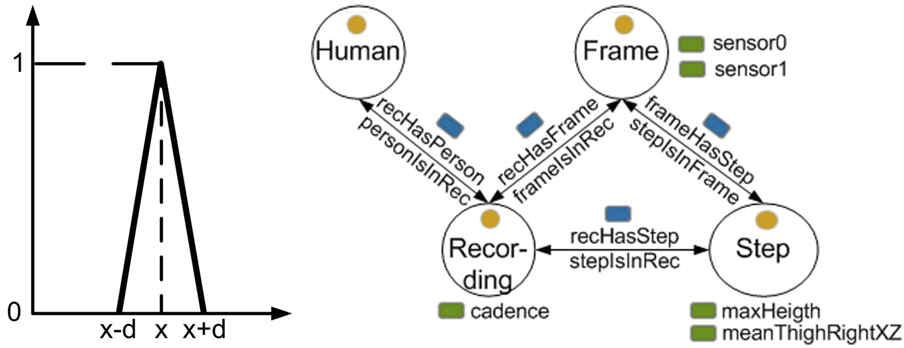

Fig. 2. (a) A triangular membership function; (b) An excerpt of our ontology.

Relationships between classes are modeled using object properties personIsInRecording, recordingHasFrame, recordingHasStep, and stepIsInFrame, together with their inverses recordingHasPerson, frameIsInRecording, stepIsInRecording, and frameHasStep, respectively. Figure 2(b) shows the classes and their relationships. We use subproperty chains to infer missing information. For example, the chain frameIsInRecording $\circ$ recordingHasStep is a subproperty of frameHasStep.

Each frame has 25 datatype properties linking it with each of the 25 joints identified by the Kinect V2 sensor. For example, sensor0 related a frame with a xsd:double number. The names of these datatype properties use the common numeration of the joints, buth we also added 25 equivalent datatype properties with more readable names. For example, spineBase is equivalent to sensor0.

Regarding the biometric features, each step has several datatype properties, such as maxHeight (of the person), or meanThighRightXZ (average value of the angles formed by the right thigh). We not only represent those attributes selected by WEKA, but also other ones such as that stepLength, or leg (left or right) that could be interesting for other people. Similarly, our ontology also allows representing biometric features of a sequence (although our Decision Module do not use them) such as the cadence (number of steps per unit of time).

Reasoning with a fuzzy ontology requires using a fuzzy reasoner. There are several implementations, one of them being *fuzzyDL* [2], accessible from the

Protégé plug-in. Firstly, it is possible to check the consistency of a fuzzy ontology. Secondly, it is possible to solve the instance retrieval problem, that is, obtaining the individuals that belong to a fuzzy concept together with their membership degrees, so we can order them and retrieve only the top-k candidates. For example, at production stage we can obtain data from a person using Kinect and then, before trying to identify him/her, retrieve the top-k individuals belonging to the fuzzy concept of people having some particular values of the attributes (e.g., a given height and a given right thigh angle) represented by means of fuzzy datatypes. Only the retrieved individuals will be transferred to the Decision Module for further processing.

Let us add some statistical information. The current schema of our fuzzy ontology has 4 classes, 8 object properties, 79 datatype properties, and 228 logical axioms. The fuzzy ontology is also populated with individuals and class/property assertions. Our ontology is not expressed in any of the tractable OWL 2 profiles: its expressivity is that of the ontology that of the Description Logic $\mathcal{ALCRIF}(\mathbf{D})$.

Decision Module. As a final step, our system contains a Decision Module that uses the response provided by the fuzzy ontology on which a classifier is applied. Several machine learning algorithms have been tested. So far, the best classification method turn out to be the k-nearest neighbor algorithm using 1 nearest neighbour and the Euclidean distance as distance for the search method for this machine learning algorithm. We used only 12 of the aggregate features computed in Sect. 3 for each step (392 steps detected in the *UPCVGait* in the preprocessing phase) and we obtained 89.03% correctly classified instances using this algorithm and 10-fold cross-validation. This result is slightly lower than 93.29%, obtained in [8] for the same dataset. However, our system can be more scalable; in [8], the search space is much bigger since they use all individuals and the entire gait sequence to classify new recordings (we use the candidates given by the fuzzy ontology and we analyze steps). Moreover, we believe that an improvement to our approach would be to introduce a voting-based scheme for the steps of a new sequence, that is, given the steps of a gait sequence, we will use the classification algorithm to classify each step, and so, each step will be a vote for one individual. The individual with more votes will be the final result of the classification.

4 Conclusions and Future Work

In this work we have summarized our ongoing research project about the combination of a gait recognition system based on Microsoft Kinect and fuzzy ontologies. We have designed an architecture for our system, developed a fuzzy ontology that makes it possible to represent Microsoft Kinect V1 and V2 data in a better way (easier to understand by humans and to reuse by intelligent applications), and discussed how to populate it with biometric features. Interestingly, for the sake of scalability, our fuzzy ontology makes it possible to reduce the number of candidates for the recognition algorithm. So far, we have only performed preliminary experiments with Microsoft Kinect V1 data, with the main differences that we use a smaller number of variables (obtained after an attribute selection to compute the most discriminant ones) and step segmentation rather than a sequence-based approach, showing promising results.

Future work will include the recording of a significant number of video sequences to develop a complete benchmark with Microsoft Kinect V2 data, making both our ontology and dataset publicly available. More experiments are also needed to evaluate *(i)* the scalability, *(ii)* the interpretability of the knowledge by humans, *(iii)* the performance of different machine learning algorithms in the framework of gait recognition systems, and *(iv)* tuning some parameters such as the width of the fuzzy triangular functions or the number of top-k candidates retrieved by the fuzzy ontology.

Acknowledgement. We were funded by DGA/FEDER and projects UZCUD 2016-TEC-02 (University of Zaragoza and Defense University Center), TIN2013-46238-C4 and TIN2016-78011-C4 (Ministerio de Economía y Competitividad).

References

1. Bobillo, F., Straccia, U.: Fuzzy ontology representation using OWL 2. Int. J. Approx. Reason. **52**(7), 1073–1094 (2011)
2. Bobillo, F., Straccia, U.: The fuzzy ontology reasoner fuzzyDL. Knowl.-Based Syst. **95**, 12–34 (2016)
3. Diaz-Rodriguez, N., Pegalajar-Cuellar, M., Lilius, J., Delgado, M.: A fuzzy ontology for semantic modelling and recognition of human behaviour. Knowl.-Based Syst. **66**, 46–60 (2014)
4. Díaz Rodríguez, N., Wikström, R., Lilius, J., Cuéllar, M.P., Delgado Calvo Flores, M.: Understanding movement and interaction: an ontology for kinect-based 3D depth sensors. In: Urzaiz, G., Ochoa, S.F., Bravo, J., Chen, L.L., Oliveira, J. (eds.) UCAmI 2013. LNCS, vol. 8276, pp. 254–261. Springer, Cham (2013). doi:10.1007/978-3-319-03176-7_33
5. Horridge, M., Tudorache, T., Nyulas, C., Vendetti, J., Noy, N.F., Musen, M.A.: WebProtege: a collaborative web-based platform for editing biomedical ontologies. Semant. Web **4**(1), 89–99 (2013)
6. Jiang, S., Wang, Y., Zhang, Y., Sun, J.: Real time gait recognition system based on Kinect skeleton feature. In: Jawahar, C.V., Shan, S. (eds.) ACCV 2014. LNCS, vol. 9008, pp. 46–57. Springer, Cham (2015). doi:10.1007/978-3-319-16628-5_4
7. Kastaniotis, D., Theodorakopoulos, I., Economou, G., Fotopoulos, S.: Gait based recognition via fusing information from euclidean and riemannian manifolds. Pattern Recogn. Lett. **84**, 245–251 (2016)
8. Kastaniotis, D., Theodorakopoulos, I., Theoharatos, C., Economou, G., Fotopoulos, S.: A framework for gait-based recognition using Kinect. Pattern Recogn. Lett. **68**(Part 2), 327–335 (2015)
9. Preis, J., Kessel, M., Werner, M., Linnhoff-Popien, C.: Gait recognition with Kinect. In: Proceedings of the 1st International Workshop on Kinect in Pervasive Computing, pp. P1–P4 (2012)

10. Smith, T.C., Frank, E.: Introducing machine learning concepts with WEKA. In: Mathé, E., Davis, S. (eds.) Statistical Genomics. MMB, vol. 1418, pp. 353–378. Springer, New York (2016). doi:10.1007/978-1-4939-3578-9_17
11. Straccia, U.: Foundations of Fuzzy Logic and Semantic Web Languages. CRC Studies in Informatics Series. Chapman & Hall, New York (2013)