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Automatic meal intake monitoring using Hidden Markov Models

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Abstract

In the latest years, the number of elderly people that has been living alone and need regular support has highly increased. Meal intake monitoring is a well-known strategy that enables premature detection of health problems. There are several attempts to develop automatic meal intake monitoring systems, but they are inadequate to monitor elderly people at home. In this context, we propose an automatic meal intake monitoring system that helps tracking people's eating behaviors, and is adequate for elderly remote monitoring at home due to its nonintrusive features. The system uses the MS Kinect sensor that provides the coordinates of the user's sitting skeleton during his meals. It analyzes the coordinates, detects eating gestures, and classifies them using Hidden Markov Models (HMMs) to estimate the user's eating behavior. A demonstrative prototype for detection and classification of gestures was implemented and tested. The detection module got satisfactory percentages of sensitivity, having a minimum of 72.7% and a maximum of 90%. The Classification module was tested with 3 proposed methods and the best method had a good average percentage of success (approximately 83%) in the classification of Soup and Main dish; regarding the left hand transporting Liquids, the results were less successful.

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Keywords: Remote monitoring, meal intake, elderly people, Microsoft Kinect, Hidden Markov Models.

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1. Introduction

Eating behavior is one of the major factors that affect health. It is known that it is not only enough to have access to food, but it is also necessary to "know how to eat". People need to know how to choose the correct type of food and the correct daily quantities along the different life phases[1]. An eating disorder represents a health risk; therefore, a healthy eating behavior and an energetic balance are key factors to have a healthy life. The process of aging submits the organism to several functional changes that affect people's health and nutritional conditions, turning a balanced eating behavior to have a higher level of importance[2]. Nowadays, populations of developed countries are aged due to the improvement of health services along as better life and work conditions[3]. In the meantime, the loneliness of elderly people has increased due to the reduction of the family number of members and the exile of young people to the main urban centers. The traditional support from family has been replaced by institutional domiciliary and personalized services. These services can be expensive mainly in scattered areas such as rural zones.

The knowledge of changes in the eating behavior allows experts to detect health problems prematurely[2]. Traditionally, eating monitoring is based in self report which is frequently considered as a burden by the participants[4]. Automatic monitoring is presented as a solution allowing to estimate the eating behavior of a user in his natural environment without the need to interact with the system. Several attempts are being developed trying to achieve automatic monitoring, but, in most of them, the user needs to use or wear special devices – they are inadequate to monitor people's meal intake, especially elderly people as they are uncomfortable and lead to disruptions in the monitoring. Specialists keep basing in manual reports produced daily in paper or, more recently, in mobile devices[5] where they ask patients to register what they eat to promote a level of self-consciousness for the situation and to develop in the patient the habit of thinking before eating. Despite of the exercise of self-consciousness they provide, these approaches present, sometimes, incorrect results as it is common that patients don't register all the ingested food for reasons such as shame, forgetfulness, or difficulty using mobile devices[6,7].

Previously, we conducted a pilot study to evaluate meal intake behavior using only the Microsoft Kinect sensor (MS Kinect)[8]. In a first phase, we made an observation of meal intake gestures, organizing them in two main types (food and liquids), and summing up their characteristics. Then, we defined an experimental scenario with the user sitting in front of a table with the MS Kinect positioned towards him. We analyzed the sitting skeleton, provided by the MS Kinect, of 3 different people with ages of 25, 84, and 85 during their meals (drinking water and eating soup and main dish). We observed that there was a relation between the user's gestures and meal intake through the analysis of distances between the hands and the head, the glass and the plate, and concluded that it would be possible to monitor the eating behavior using this sensor.

In this paper, we propose an automatic meal intake monitoring system that helps tracking people's eating behaviors that is adequate for elderly remote monitoring at home due to its nonintrusive features. This paper is organized as follows: in section 2, we present a literature review about automatic meal intake monitoring and present the background on HMMs, in section 3, we present the architecture of the proposed system, in section 4, we present the obtained results, and, in section 5, we present our conclusions and future work.

2. Literature review

2.1. Automatic meal intake monitoring

The first approach to solve the problem of traditional meal intake monitoring methods was to simplify the registration of the ingested food. Siek[9], used voice recorders and barcode readers, although, the results indicated that participants with low literacy skills had difficulties describing food items in voice recordings.

The next step was to develop automatic meal intake, monitoring approaches, aiming at removing the need for the users to register the food they ingested by themselves, through the usage of several different sensors:

Gao[10], aimed at measuring the feeding difficulties of patients in a nursing home. The main goal was to automatically count the number of gestures made to the mouth (food transportation) through computer vision techniques. In this work, a segmentation algorithm was developed to provide features to the system.

Patterson[11], aimed at exploring the interaction with objects to trace the user's morning activities. It was intended, for instance, to recognize not only if the user was cooking but what he was cooking. In total, the authors studied 11 different activities, including the preparation and consumption of breakfast. The author used Radio-Frequency IDentification (RFID) tags for identification in 60 household objects and a tag reader placed in the user's hand.

Chang[12], aimed at monitoring the transport of food from containers to the plate. The author used a table with RFID sensors to identify food containers that contained different types of food, and a weighting surface embedded on a common table. By reading the RFID tags, it is possible to obtain the food’s nutritional information as the number of calories and, with the weighting sensors, it is possible to estimate the ingested quantities.

Amft[13], used a combination of body sensors to study different phases of the user’s behavior during a meal, including a motion sensor jacket, to track intake gestures, a mini microphone to record chewing sounds, and collar-based sensors on the throat to detect swallowing movements.

Hondori[14], developed a system to help post-stroke patients completing their daily activities, independently and in a cheaper way. This approach detects the ingestion of food and liquids in the patient’s home. The developed system uses the Microsoft Kinect sensor alongside inertial sensors placed in the cutlery and in the mug.

Zhou[15], used a smart dining tray to provide information of the food’s weight, through pressure sensors placed underneath the plate. The pressure information was also used to distinguish between various cutlery-related activities, such as cutting, poking, stirring, or scooping.

Thomaz[16], contributes towards the implementation of a practical, automated system, for everyday food intake monitoring, using a wrist-mounted inertial sensor to recognize eating moments, based on 3-axis accelerometry collected with a popular off-the-shelf smartwatch.

2.2. Background

HMMs have been successfully applied in the context of gesture recognition because they are appropriate to deal with their random properties. A HMM is a statistical model with unknown parameters and its purpose consists in determining these parameters from the observable ones[17]. They are used to represent gestures and their parameters are learned from their training information. Based on the most likely performance criterion, the gestures are recognized, evaluating the trained HMMs. The model has the name “hidden” because all you can see is only a sequence of observations[18]. There are 5 elements needed to create a HMM[19]: N, the number of states in the model; M, the number of distinct observation symbols per state; A, the state transition probability distribution; B, the observation symbol probability distribution; and π, the initial state distribution. A HMM can be created with different structures as the ergodic, linear, left-to-right, Bakis and parallel. The structures vary from what states can be reached in each transition[19,20,21] and there are 3 problems HMMs can solve[22]: evaluation, decoding and learning.

3. System architecture

The meal intake monitoring system was thought to work in a scenario where the user sits in front of a table to take his daily meals (Fig. 1 – a). A MS Kinect is positioned in front of a table to track the user’s skeleton and to send its coordinates to the system. The system is composed by 4 modules (Fig. 1 – b): Gesture segmentation, that segments incoming coordinates to detect gestures; Preprocessing, that normalizes coordinates; Gesture classification, that identifies the gestures; and Meal estimation, that provides an estimate of the ingested food.

(a)

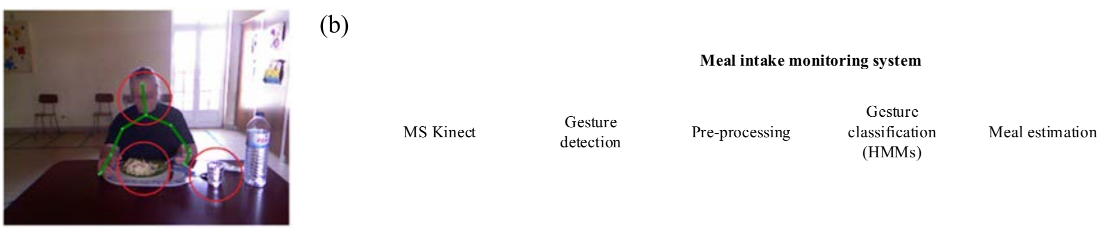

Fig. 1. (a) Scenario with skeleton mapping and key zones of gesture detection. (b) Meal intake monitoring system.

3.1. Scenario

This study tries to replicate, in the lab, the meal condition of an elderly person living alone. We envision the user sitting in his living room, watching TV, while having a meal – possibly a pre-prepared meal brought by a community center. The MS Kinect is positioned in front of him, at a distance of 1.2 meters from the user, at a height of 1.2 meters from the floor, and with a tilt of -10 degrees. It automatically detects the user's sitting skeleton representing 10 different joints: hands, wrists, elbows, shoulders, shoulder center, and head.

3.2. Gesture detection and segmentation

A meal intake gesture consists in a movement of one of the hands from the plate or glass zone to the mouth. In order to the Gesture detection module work, we marked the zones of the plate and the glass (Fig. 1 – a, red circles). The module computes the distances from the position of the hands to the head, the plate, and the glass. Based on those distances and their variation in time (speed) the module segments each candidate gesture. A sequence of coordinates will be considered as a candidate gesture if the distances between the hands and plate (or the glass) are less than a d_{Min} and with an average duration in the interval $[t_{min}, t_{max}]$.

3.3. Pre-processing

To normalize the joints coordinates, we chose to perform an initial 3D pre-processing similar to the one made by Nattee[23] in 2D. This process is composed by 5 different phases: duplicate point elimination, size normalization, smoothing, speed normalization, and conversion to rectangular coordinates to 40 direction symbols.

1) Duplicate point elimination: deletes all points that have the same XYZ coordinates as the previous point in the sequence.
2) Size normalization: normalizes the coordinates within the [0, 1]. The XY coordinates provided by MS Kinect are represented in a 640x480 image and the Z coordinate is the distance to the sensor in millimeters.
3) Smoothing: smoothing is used to reduce signal high frequency noise. We calculated the average of each point with the previous and next ones.
4) Speed normalization: removes the influence of speed in the trajectory and puts the points equally spaced.

In Fig. 2, we present a graphical representation of these first phases of the Pre-processing.

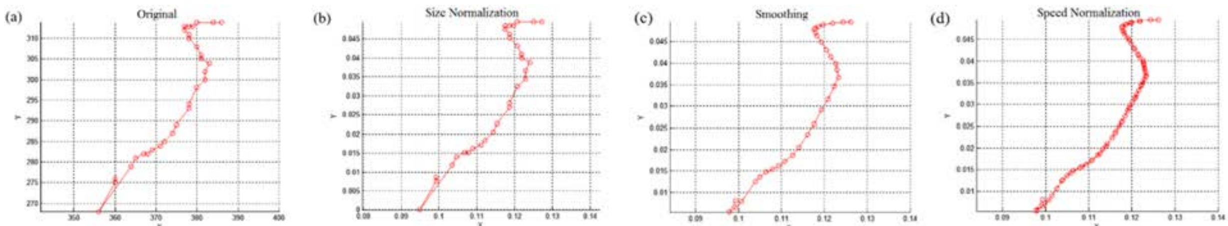

Fig. 2. Pre-processing phases: (a) Original signal, (b) Size Normalization, (c) Smoothing, and (d) Speed Normalization.

As we can see in phase (b), the normalization resulted in a scale change; in phase (c), the points slightly changed their position making the trajectory smoother; and in the phase (d), the trajectory has a larger number of points equally spaced.

5) Conversion of XYZ coordinates to 40 direction symbols: we use 39 symbols to represent the trajectory progression in different directions and one more to represent no progression in the trajectory.

3.4. Gesture classification

Candidate gestures are processed in 5 HMM sub-modules in order to calculate the probability, of a given gesture, relatively to the different HMMs which represent the considered types of meal gestures: transport of soup from the plate to the mouth (using the right hand), transport of main dish (using the right hand), transport of main dish (using the left hand), liquids transportation from the glass to the mouth (using the right hand) and liquids transportation (using the left hand). We considered the soup type using only the right hand as, from the acquired data, all the participants used the right hand.

The HMM having the highest probability of generating the sequence of values of the given gesture will be the one characterizing the gesture. With HMMs we are able to calculate the probability of a given sequence having been generated by the respective HMM. Each one of the 5 HMM sub-modules has 7 HMMs (one for each one of the joints: hands, elbows, shoulders and shoulder center), existing a total of 5 × 7 = 35 HMMs. We have discarded the joints of the head as this one remained barely static during the performed tests and has a similar behavior as the shoulder center one, and the joints of the wrists which have a parallel behavior as the hands. As observations, we used the coordinates of the joints, pre-processed and represented with 40 directions. All HMMs have 5 states with an ergodic structure (Fig. 3).

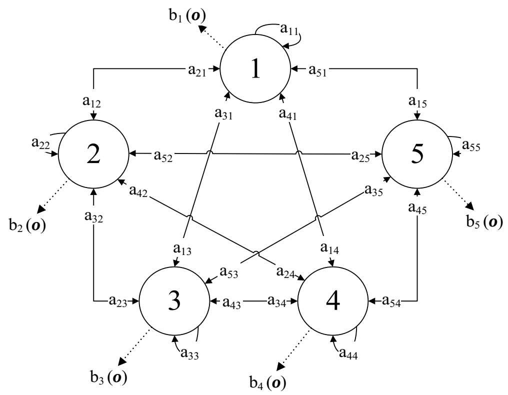

Fig. 3. State diagram of the HMMs.

As the result from each gesture evaluation, we obtain 35 probabilities that represent the probability of each HMM generating the given sequence. For each one of the 5 different type of gestures, we obtain 7 different values in each HMM sub-module, one for each joint. These values are negative and represent the probability through a logarithmic notation. This is frequently used in this type of calculations due to the fact that this process, using logarithmic sums, is computationally lighter in opposite of using multiplications that are traditionally used. The sub-module HMM having the highest probability for each joint will be classified has having generated the gesture.

So far, we obtain the probabilities for each individual joint, although, that turned out to be insufficient as using the classification of each joint alone, we obtain only around 50% of correct classifications. Therefore, we need a global classification with all the joints. To achieve this, we proposed three different methods:

1) Method 1 – Count occurrences: we count the number of occurrences of the maximum probabilities for each sub-module HMM and the one having the largest number will classify the gesture. Although, there's the possibility of existing 2 or 3 types of gestures with the same number of occurrences. For that, we analyzed the gestures used for training the models, classified them and designed a tiebreaker table by counting the number of tie occurrences and identification of the corresponding gesture.
2) Method 2 – Weighted classification of the right and left arms: the classification is made by separating the right arm (right hand, right elbow and right shoulder joints) and the left arm (left hand, left elbow and left shoulder joints) – we don't take in consideration the shoulder center joint in this method. For each arm, we assigned a relevance factor for each one of their joints which allows us to classify the arm through the classification of the HMMs. When the classification of the arms is different, we used a decision table obtained based on the classification of the training gestures. For the combinations that didn't happen in the training gestures, we opted by using the classification of the right arm to classify the gesture.
3) Method 3 – Right hand gestures vs. left hand gestures: we count the number of occurrences separately for the gestures performed with right hand [Soup, Main dish (right hand) and Liquids (right hand)] and for the gestures

performed with the left hand [Main dish (left hand) and Liquids (left hand)] referring to the respective arm. The hand of the arm having more occurrences will classify the gesture. In case of, in the deciding arm, the hand has a classification of a gesture performed with the opposite arm, the deciding role will be passed to the elbow and successively to the shoulder. If the number of occurrences is the same, the hand of the arm having more occurrences of the same type will classify the gesture. In case there continues to be a tie, we defined that the right hand (joint with the most correct classifications in the training gestures) will classify the gesture. In this method we also don't consider the shoulder center joint.

3.5. Meal estimation

This module estimates the user's behavior (type and quantity of ingested food and eating habits) based on the number of gestures classified in the previous module. By counting the number of gestures, it is possible to estimate the quantity and what type of food the user has ingested.

To explain the functioning of this module, let's consider the acquired meals with the respective number of gestures for the 3 types. By observing those values and assuming the user averagely ingests the same amount of food in all meals, we concluded that, for ingesting a complete soup type of meal, in average, the user performs 36 transport gestures; for a complete of the main dish, the user performs 49 gestures and, for a complete of liquids (a full glass of water), the user performs 6 gestures. Therefore, let's assume, during a meal, the system recognized 30 soup gestures, 35 main dish gestures and 3 liquid gestures. We can then estimate that the user ingested 83.34% of a soup type of meal, 71.43% of a main dish type of meal and 50% of a liquid type of meal (half glass of water).

4. Results

We tested the detection and classification modules of the proposed system with acquired data of different participants with ages of 22, 23, 25, 47, 84, and 85 years old during their meals - drinking water, eating soup and eating main dish. In total we had 7 sequences of the type Soup, 2 of the Main dish (right hand), 6 of the Main dish (left hand), 15 of the Liquids (right hand), and 5 of the Liquids (left hand). Note that we were able to acquired only 2 sequences for the Main dish (right hand) as most people eat the main dish using a fork in the left hand.

We started testing the classification module by creating a ground-true with a set of 689 acquired gestures manually segmented. 242 irregular motion gestures were discarded. The 447 valid gestures were organized and joined by type of meal independently of the person who performed them. For each type, of every sequence, we used 2 thirds of the gestures to train the HMMs and the remaining one for evaluation. Then, we evaluated the detection module with the 689 gestures.

4.1. Gesture detection and segmentation

In the gesture detection module the tests were performed counting the true positives (TP), false positives (FP) and false negatives (FN) for each type of meal. The TP are the percentage of gestures that method detected and the participant performed the gesture; the FP are the percentage of gestures that method detected but the participant didn't perform the gesture; and FN are the percentage of gestures that the method didn't detect but the participant performed a gesture. Table 1 presents the results of the detection module.

Table 1. Average percentage of correct, incorrect and missed detections.

Type of meal	TP %	FP %	FN %
Soup	79%	9%	21%
Main dish (right hand)	73%	17%	27%
Main dish (left hand)	75%	42%	25%
Liquids (right hand)	90%	5%	10%
Liquids (left hand)	85%	15%	15%

In the Soup, we got a good representation of the meal with 79% TP and 9% of FP. In the Main dish, the meal gestures detection was satisfactory (73% and 75% TP) but a large number of none eating gestures were detected: in the right hand, 17% FP, which is a bit high, and, in the left hand, 42%, which is very high. Finally, in the Liquids, we got a very good representation of the meal, 90% and 85% TP, and a short number of none eating gestures, 5% and 15%. Weaker results were obtained in the Main dish because the gestures are made with both hands simultaneously near the plate and the MS Kinect's skeleton mapping is more susceptible to generate errors in the joints' positions.

4.2. Gesture classification

The gesture classification module tests were made with the 3 methods presented in 3.4 and the results are summed up in Table 2.

Table 2. Average success percentage for the three methods.

Type of meal	Method 1	Method 2	Method 3
Soup	78.3%	80.4%	69.6%
Main dish (right hand)	80.0%	40.0%	74.3%
Main dish (left hand)	74.7%	71.8%	61.5%
Liquids (right hand)	83.3%	72.2%	66.7%
Liquids (left hand)	16.7%	0.0%	50.0%

In the Soup, Method 1 and Method 2 obtained the best performance, 78.3% and 80.4%, followed by Method 3 with less 8.7%. In the Main dish, Method 1 was the best, 80% and 74.7%, although Method 3 obtained 74.3% in the right hand, and Method 2 obtained 71.8% in the left hand. Finally, in the Liquids, only the right hand had satisfactory classifications. Method 1 obtained 83.3% followed by Method 2 and Method 1, respectively, 11.1% and 16.6%. The left hand got the best classification with Method 3 but only with a 50%. In general, Method 1 presented the best results followed by the Method 2.

We looked closely to results and verified that in several cases the gestures were classified in the wrong hand but in the right main type of meal, e.g., a gesture of Main dish (right hand) was wrongly classified as Main dish (left hand). So we decided to reclassify the gestures using the 3 methods independently of the hand that was used. With this process, we obtained 87.8%, 79.7%, and 78.4% for Main dish, and 56.7%, 46.6%, and 60.0% for Liquids, respectively for Method 1, Method 2, and Method 3. We obtained an improvement in all methods, particularly in Liquids. The best method for the classification of the Main dish was Method 1 and for Liquids, the best method was Method 3.

5. Conclusions and future work

In this paper, we propose an automatic meal intake monitoring system that helps tracking people's eating behaviors, and which we believe to be adequate for monitoring older people remotely at home. The system analyzes the coordinates obtained with a MS Kinect, detects eating gestures, and classifies them using Hidden Markov Models (HMMs). A demonstrative prototype was implemented and tested with meals of 8 different users. The Meal estimation module was not implemented.

The system was tested with 689 eating gestures. For the detection module, we got satisfactory results for Liquids and Soup. Weaker results were obtained in the Main dish because the gestures are made with both hands simultaneously near the plate and the MS Kinect's skeleton mapping is more susceptible to generate errors in the joints' positions. The Classification module was tested with 3 proposed methods, and, in general, Method 1 presented the best results followed by Method 2. Soup and Main dish had good correct classification percentages but in Liquids, particularly in the left hand of Liquids, it was weak. After verifying that in several cases the gestures were classified in the wrong hand but in the right main type of meal, a reclassification was made for Main dish and Liquids, independently of the hand, which resulted in an improvement of all classifications.

For future work, we would like to improve the proposed detection and classification modules as we think that they can be improved. In this paper, all gestures of the same type, performed by different people, were put together to train and test the classification module. However, if we use only gestures of each person, it would improve the results. We would also like to implement and test the Meal estimation module, this way we could test the system in a real scenario.

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