Chapter 219
Ambient, On-Body, and Implantable Monitoring Technologies to Assess Dietary Behavior

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Abbreviations

ADM	Automatic Dietary Monitoring
EGG	Electrogastrography
EMG	Electromyography
PDA	Personal Digital Assistant
RFID	Radio-frequency-identification

219.1 Introduction

Dietary behavior subsumes all the complex habitual choices of an individual when selecting and consuming food. Monitoring this behavior is a prerequisite for effective diagnosis, prevention, and intervention in nutritional research (Bellisle 2003). Monitoring assessments for dietary behavior have a long tradition in questionnaires (Burke 1947), although their merit has long been doubted in the 1960s and 1970s (Willett 1994). The diversity of diet assessment methodologies based on questionnaires can be characterized according to their monitoring horizon and resolution. Coarse, long-term behavior assessments are captured by food frequency questionnaires; short-term and immediate assessments include short-term recalls and self-reports (Biro et al. 2002). Food-frequency assessments have been designed for epidemiology studies to capture food consummation history of months to several years (Willett 1990). In contrast, short-term recalls and self-reports typically quantify food consumption during a single day. For short-term recalls, this is achieved through specific questions of an interviewer, while self-reports are completed by the respondent (Witschi 1990).

Weight loss and other dietary behavior coaching programs rely on actual behavior information to educate modifications of accustomed lifestyle (Wylie-Rosett et al. 1990). However, changing lifestyle is a tough challenge for the individual, which requires continuous, potentially life-long coaching assistance (Paineau et al. 2008). Self-reports are frequently used in coaching programs since they aim to acquire information on time of food consumption, food product, and amounts in the temporal resolution of individual meal and snack intakes. Such actual information was found particularly useful to

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adapt feedback in coaching programs and has been identified to improve coaching success rates (Oenema and Brug 2003). While self-reports *could* capture the dietary behavior in temporal resolution and information detail adequate for coaching programs, they practically fail due to the considerable labor of manual logging required by the respondent (Witschi 1990). Often accuracy is hampered due to the respondent's motivation, memorizing, or literate capabilities. Moreover, respondents are influenced by the changing perceptions of desirability and increasing self-awareness due to the reporting. In turn, food details that could be interpreted as abnormal or unhealthy are omitted and snacks will be forgotten. Reporting errors varied between 50% of under- and overestimation (Schoeller 1995; Hill and Davies 2001; Westerterp and Goris 2002). Although participant effort and large errors render self-reports infeasible for monitoring durations longer than 1 week (Witschi 1990), they are used in several-month coaching programs. Similarly impractical, the effort and cost of respondent and interviewer to maintain short-term recalls are not viable for several-month monitoring periods.

The practical effectiveness of programs targeting dietary behavioral changes is often very low. Only 20% of the participants in a study, who initially achieved at least a 10% body weight reduction, were able to maintain the new weight after 1 year (Wing and Phelan 2005). While improved success is expected through longer study durations of 2–5 years, it is today not clear how these should be achieved using conventional dietary behavior assessments. Novel and robust dietary monitoring could play an essential role in enabling long-term or permanent dietary assistance. However, novel monitoring solutions are not only needed to help combat the pandemic of overweight and obesity, but also to support patients with various diet-related diseases, including anorexia nervosa, binge eating, bulimia, orthorexia, and others (Berkman et al. 2006). To this end, various physiological, psychological, and social constraints influence dietary behavior (Jequier and Tappy 1999), which stimulates the comprehensive monitoring need. Geriatric patients may serve as one example of a particularly affected group: in a sample of 298 patients, 93% were found to be malnourished, due to various co-conditions (Rypkema et al. 2004). Long-term or permanent dietary assistance in this group – and similarly in many of the aforementioned ones – cannot be achieved by classic assessment techniques. Instead, automated reminders that are adaptive to the individual's habits could provide this support.

Since the mid-1990s, many attempts aimed at replacing classic paper-based questionnaires with computer-based solutions (Ngo et al. 2009). Furthermore, since the early 2000s, novel ubiquitous technologies have addressed the vision of alleviating respondents entirely from manual food-intake reporting in natural, out-of-lab settings. The latter efforts have been framed under the name Automatic Dietary Monitoring (ADM) (Amft et al. 2005b; Amft and Tröster 2009). Although many of the ADM approaches have yet to be refined and validated in dietary programs and trials, their contribution toward long-term dietary assistance is very promising. This chapter reviews sensing and information technology concepts that have been demonstrated, or are applicable for dietary behavior assessment in monitoring programs and out-of-lab studies. Attributes of the underlying principles are summarized and constraints of individual monitoring concepts identified. A taxonomy is introduced to categorize fundamental approaches in dietary behavior monitoring technologies.

219.2 A Taxonomy of Dietary Monitoring Technology

Similar to paper-based assessments, computer-based manual monitoring techniques require that the respondent completes forms and questions with details on personal dietary behavior. Thus, both approaches can be described as manual monitoring concepts. In contrast, the automatic concept (ADM) attempts to derive dietary behavior information from sensors and information processing and sensor pattern recognition algorithms. The ADM concept can be further categorized with regard to the used sensor locations in on-body and implantable versus ambient installed technologies. Both approaches

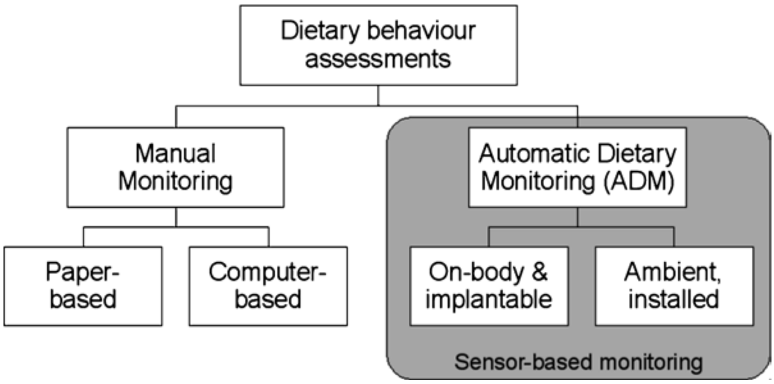

Fig. 219.1 Dietary monitoring technology taxonomy. Paper- and computer-based assessments require that respondents complete forms with their daily details on dietary behavior. Thus, both approaches can be categorized as manual monitoring concepts. In contrast, the automatic concept (Automatic Dietary Monitoring, ADM) requires that dietary behavior information is obtained from sensor and information processing algorithms. The ADM concept can be further discriminated regarding the sensor location in on-body and implantable vs. ambient monitoring technologies. Both have individual properties that determine their usage options and limitations

have particular properties that determine their usage options and limitations. These properties are detailed in subsequent sections. Figure 219.1 illustrates this dietary monitoring taxonomy.

A second essential categorization of dietary assessments that affects both manual and automatic diet assessments is related to the targeted monitoring information detail and resolution. Assessments that capture individual intake events can acquire behavior information immediately at the event. These assessments can either request that the respondent completes a questionnaire during or subsequent to the intake event, e.g., using self-reports. In the case of ADM, sensor information is used to identify the intake event and its details. Intake event assessments provide actual dietary behavior information; hence these methods can indicate short-term changes in habitual patterns. In contrast to the individual intake information acquired by the individual events approach, frequency assessments aim to derive dietary behavior history over a period of several weeks and months through recall techniques. The information provided by frequency and history assessments is far less detailed compared to the fine-grained individual event assessments. Figure 219.2 illustrates the two categories.

Computer-based manual monitoring technologies have been applied for frequency assessments, primarily to reduce the respondent effort with regard to paper-based assessments. The primary benefit of ADM-based solutions is to obtain individual event details. Nevertheless, ADM could also be applied to accumulate behavioral information over periods of weeks and months and thus resemble classic frequency assessments in the future.

219.3 Dietary Behavior Dimensions: What to Assess?

Based on their historical development, paper-based questionnaire assessments have a broad relevance in current monitoring programs and research studies. Monitoring technologies that aim to supplement or even replace questionnaire assessments are frequently aligning their information to the monitoring dimensions captured in short-term recalls and self-reports. These dietary behavior dimensions include:

- **Intake schedule:** The timing of food consumption reveals essential information on daily rhythm and accomplishment of daily routines in diet program participants (de Castro 2004). Moreover, the duration of intake sessions can help to identify behavioral and metabolic situation (Bechtold 2008).

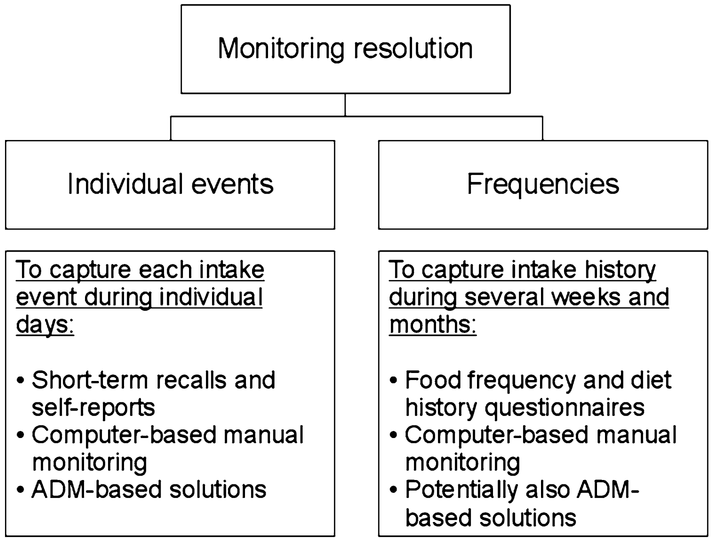

Fig. 219.2 Monitoring resolution of dietary behavior assessments. An essential categorization of dietary assessments is the targeted monitoring resolution. Assessments targeting individual intake events acquire information often immediately at the event. The assessment can either request that the respondent completes a questionnaire subsequently to the intake event in self-reports, or – in the case of ADM – use sensor information to identify the intake event and its details. As opposed to individual intake information, frequency assessments aim to derive dietary behavior history over a period of weeks or months through recall questionnaires. The information provided by history assessments is far less detailed compared to the fine-grained individual event assessments

- **Eating microstructure:** The eating microstructure describes the interaction of chewing, oral bolus formation, tongue activity, and swallowing. This structure can identify the stimulation to eat, sensory food interactions and perception, and mental influences on consumption (Aguilera 2005). As an extension, the intake microstructure includes the feeding activity through arm motion and food ingestion (Amft et al. 2007a). The eating microstructure has been identified as a source of information in satiation processes (Kissileff and Guss 2001).
- **Meal composition and preparation:** The choice of foods is a prominent determinant of personal diet and important biomarker assessment criteria in epidemiology (Sandström 2001). Food product and type information reveals calorie and nutrient consumption, including vitamins, minerals, and water, which are essential metabolic elements (Willett 1990). Food can be profoundly altered by preparation and alternations, and as a consequence influence palatability, material structure, nutrient content, and alert food safety issues (Fischer et al. 2007). In manual monitoring assessments, food type and products are often literally described or selected by matching similar items from a predefined food list.
- **Food amount:** In assessing food balance, quantified food amounts are an essential information (Epstein et al. 2009). In combination with food type or product information, it permits estimation of consumed calories. In manual monitoring assessments, food amount is determined by weighting items, or through coarse quantification of food pieces.

Monitoring of the dietary behavior dimensions becomes most effective for coaching, if it is captured at the detail level of individual meal and snack intakes. To this end, short-term recalls and self-reports provide the fundamental basis for most computer-based manual and ADM-based monitoring technologies. Thus, the technologies must sustain the variability and operational requirement of the user's natural daily routine, while conveniently capturing intake activities at this fine-grained resolution.

219.4 Monitoring Technologies: Options and Limits

The diversity and variability of individual dietary behavior has been the primary challenge for developing adequate questionnaire assessments that could measure it (Willett 1994). Despite the long-standing development, assessing particular aspects of intake, such as the consumed energy or particular biomarkers is still highly complicated (Hill and Davies 2001; Westerterp and Goris 2002). For calorie-constraint diets, it requires reporting of consumed calories – or at least the exact food products – in combination with their amount. Moreover, reporting may become entirely impractical for homemade meals, or foods acquired from farmer markets.

Diversity and variability challenges apply to technology-based monitoring as well. Technologies are similarly exposed to variable daily routines, in which users are focused on their routine-related activity. In analogy to the shortcomings of classic paper-and-pencil-based questionnaires, any interference that monitoring technologies may impose on the user's habitual activities, can hamper their use and viability in diet coaching programs. Nevertheless, technology can provide several advantages compared to classic paper-based assessments, including potentially improved user convenience, new monitoring features and information, and even enable diet monitoring in unsupervised settings, where it has not been feasible before. Options and limitations of technology-based monitoring can be grouped as follows:

- **Requirements for reporting and interaction:** The need for frequent interaction and focus has been the classical constraint of manual monitoring assessments. The stringent continuous self-reporting of every food intake was observed to be a burden, interfering with the user's activities in natural settings. This challenge similarly affects computer-based manual assessments, as described below. ADM solutions specifically aim to minimize or entirely remove interaction requirements for consumption reporting and thus allow focusing all interaction on the coaching.
- **Comfort and convenience of use:** Comfort is essentially determined by the monitoring influence during daily activity and routine. While paper-based questionnaires required carrying forms and a pen, computer-based manual assessments increased comfort as the respondent could use a PDA or mobile phone device that is often considered a commodity and permanent accessory (Amft and Lukowicz 2009). ADM solutions use sensors, which could be considered alien in the user's habitual setting. Thus, ADM requires to specifically address the integration of sensor and processing technology in daily life, such as clothing, environments, and objects that are typically used.
- **Responsiveness and information detail:** Compared to classic paper-based questionnaires, monitoring technologies provide the intrinsic advantage of an immediate response option in reaction to acquired information (either manually entered to automatically sensed). The response service could be individually tailored by a dietitian and provided autonomously, based on pre-configured coaching concepts. Moreover, ADM-based solutions can provide information on dietary behavior dimensions that were hardly available through classic assessments. This particularly includes details of the eating microstructure, and advanced options to assess food and intake perception.
- **Information quality and system robustness:** Quality of monitored information is a critical constraint that affects all assessments, due to the aforementioned challenges in dietary behavior. Questionnaire assessments generally suffer from gradual worsening in acquired information due to continuously required efforts and changing perception of desirability. In the ADM approach, information quality is determined by the selected sensor and information extraction algorithms. ADM

has conceptual advantages for obtaining high information quality, in contrast to manual methods that can be biased by personality traits. However, when compared to computer-based questionnaires, system complexity – and with it, system robustness concerns – are elevated in ADM.

219.5 ADM Technologies: Options and Limits

Being the most advanced monitoring concept, ADM aims to pursue an entirely autonomous approach in acquiring dietary behavior information from sensor data. The diversity and variability challenges prevent that a single sensor could capture all dimensions of dietary behavior sufficiently. Consequently, ADM-based solutions often address particular dimensions of dietary behavior, such as monitoring the amount of consumed food using a plate-integrated weight scale or assessing the eating microstructure using a pressure-sensing tooth implant.

According to the taxonomy of dietary monitoring technologies (see Fig. 219.1), ADM solutions can be further distinguished regarding the sensing locations used, in on-body and implantable versus ambient monitoring assessments. Ambient ADM solutions have been demonstrated to provide dietary behavior information on dimensions that are difficult to assess with on- or in-body approaches. A particular example of an ambient ADM solution is to estimate consumed food amounts using a plate-integrated weight scale. In contrast, on-body and implantable ADM solutions allow to assess detailed parameters of the eating microstructure dimension, such as the chewing frequency.

Pure ambient monitoring technologies lack the option to associate sensor data directly with a particular person (Amft and Tröster 2009). For example, the weighting-plate could be shared by family members and thus provide misleading information for personal coaching.

On-body and implantable ADM solutions are not constraint to a particular location of the individual. Location-independent monitoring is an important property for assessing dietary behavior in modern lifestyles, which often involves consumption at various places during daily routine (Table 219.1).

Table 219.1 Comparison of on-body and implantable vs. ambient ADM properties

<table>
<tr><th colspan="2">Automatic dietary monitoring (ADM)</th></tr>
<tr><th>On-body and implantable</th><th>Ambient, installed</th></tr>
<tr><td>Sensor-based monitoring techniques that can be integrated into clothing (wearable), attached to the body, or implanted into the body
• Dietary behavior dimensions. All addressed, currently with limitations, e.g., for meal composition and food amount estimation. Provides detailed information on eating microstructure (e.g. chewing frequency)
• Responsiveness. Immediate response possible through a central mobile unit (e.g., a mobile phone)
• Comfort and convenience of use. Systems are at risk of being considered alien and obtrusive in daily activities
• Information quality and system robustness. Solutions are not location-dependent, but affected by daily activities</td><td>Sensor-based monitoring techniques that can be embedded into dining-related environments and objects
• Dietary behavior dimensions. All addressed, with limitations regarding full coverage of daily dietary activities
• Responsiveness and information detail. Immediate response requires combination with on-body devices or ambient information feedback (e.g.. displays)
• Comfort and convenience of use. Systems are at risk of being considered alien in personal environments
• Information quality and system robustness. Lack option to associate sensor data directly with particular person</td></tr>
</table>

Automatic dietary monitoring summarizes sensor-based monitoring approaches of dietary behaviour that can autonomously derive information on at least one dietary behaviour dimension. It targets to alleviate the respondent's effort, while providing more information details and higher information quality compared to manual techniques. The table summarizes properties of two ADM categories (on-body and implantable vs. ambient installed ADM solutions), according to their options and limitations

219.5.1 Approaches in Computer-Based Manual Monitoring Technologies

Computer-based reporting techniques were developed due to the need of unbiased dietary assessments in clinical and epidemiological studies. A systematic review classified study designs using computer-based manual assessments into computerized assessment; personal digital assistants (PDA), digital photography, and smart cards (Ngo et al. 2009). Here, the acquired dietary behavior dimensions are summarized and application constraints of individual concepts identified. According to the previously presented technology-oriented taxonomy, techniques based on smart cards (purchase registry) belong to ADM-based techniques and thus will be discussed as ambient ADM monitoring technology below.

Computerized questionnaires: Computerized questionnaires have been designed to resemble paper-based questionnaires and applied for both intake event and frequency assessments. The main advantages of computerized questionnaires compared to the paper-based originals are that computers ease information entry, by offering food-type selections and simple push-button answer options. Further information processing is simplified since the respondent's entries are digital (Burke et al. 2005). Moreover, the questionnaires can be implemented on PDAs and mobile phones, and thus enable intake event diaries. The assessment can also be realized as Internet-based application, thus enabling the use in large study populations, e.g., in epidemiological studies.

Several studies have applied computerized questionnaires, including the BalanceLog and DietMatePro systems (Burke et al. 2005). Several studies combined the manual computer entry with additional technologies to improve information detail, including digital photography, audio recordings, and shopping receipt scanning. The studies found that challenges of classic paper-based assessments remain, such as the constraints to literacy capability of the respondents and effort to maintain diary assessment over extended periods. In addition, computerized questionnaires can introduce additional challenges, including the need for computer training, multiple entries in simple push-button solutions, as well as software and hardware issues (Burke et al. 2005). Findings showed that computerized questionnaires using PDAs have no benefits over paper-based approaches in improving reporting validity, but could improve adherence (Yon et al. 2006; Beasley 2007).

Based on their origin from paper-based approaches, computerized questionnaires can provide intake schedule, food composition and preparation, as well as amount information.

Digital photography: Photographs of the food plate, before and after consumption has been used to assess meal composition and consumed food amounts. Thus, photography provides an alternative to food item weighting and categorization techniques. The pictures are linked to intake reports, e.g., using computerized questionnaires, transmitted for analysis, and there are either manually evaluated or assessed by computer-based image content analysis algorithms. The approach requires reference photos of all considered food items, in both manual and computer-based analysis.

Several systems have been investigated that include the photography technique in PDAs and mobile phones (Kikunaga et al. 2007; Martin et al. 2009). While this technique reduces respondent efforts, the studies observed underreporting and varying correlations between the photography approach and weighted food self-reports. Particular challenges of the photography technique are the availability of reference photos and that pictures must be taken from the same angle as the references to support the analysis (Ngo et al. 2009).

Digital photography is beneficial for estimating dietary activities (intake schedule form the photography time), meal composition, and food amount (by analyzing plate pictures before and after consumption). Computer-based analysis algorithms need to be developed to automate the picture analysis (Shroff et al. 2008).

Audio recordings: To erase the respondent in describing dietary behavior, voice recordings were used, either in combination with computerized questionnaires or by sound-recorded questions. This technique reduces the reporting burden for respondents, but increases difficulty for study observers analyzing the data. Nevertheless, it has clear advantages, in particular among respondents with handicaps or limited literate capabilities.

Studies using voice recorders or PDAs showed that the technique can be enjoyable for respondents (Ngo et al. 2009), but challenges in describing food items or meal compositions as well as backward-logging remain (Siek et al. 2006).

Audio recordings are beneficial for estimating meal composition and can support the acquisition of other dietary behavior dimensions.

Shopping receipt and bar code scanning: Alternatives to assess food composition is to scan food product purchase receipts or bar codes of individual products. This technique lends itself to frequency and consumption history assessments, as individual purchases can be subsumed.

Bar code scanning was used in different studies, indicating a benefit of the method to acquire more information on food selections (Welch et al. 2009; Siek et al. 2006). Nevertheless, the technique requires training with the scanner and may be limited due to unknown bar codes. Consumption estimates from shopping receipt and bar code scanning can be misleading when purchases are shared among multiple family members.

Shopping receipt and bar code scanning are beneficial to indirectly estimate meal composition and food amounts.

219.5.1.1 Key Features of Computer-Based Manual Monitoring Technologies

1. Computerized questionnaires are developed from classic paper-and-pencil questionnaire assessments and require manual entry of dietary behavior information into electronic devices, including PDAs, mobile phones, and into Internet websites.
2. Additional manual recording forms have been developed and evaluated in studies, including digital photography, audio recordings, and shopping receipt and bar code scanning. These techniques are used, depending on the study setting and participant population, to complement questionnaire assessments.
3. The techniques ease the respondent's efforts in reporting and increase motivation. However, the requirement for stringent continuous reporting of dietary behavior by respondents remains.
4. Computerized questionnaires using PDAs have no revealed benefits over paper-based approaches in improving reporting validity, but could improve respondent adherence.
5. Research on obtaining viable computer-based manual monitoring techniques for study assessments is ongoing.

219.5.2 Approaches in On-Body and Implantable Monitoring Technologies

Some of the on-body and implantable monitoring technologies are illustrated in Fig. 219.3.

Intake motions: Movements of the upper body, including arms, trunk, and head, are required for most forms of intake. Movements can be separated into a coarse preparation of food or beverage items, such as unpacking, cooking, and plate loading, and motions targeting intake. Food intake motions of the arms include fine-cutting and maneuvering prepared food pieces to the mouth. During the intake phase, utensils are used, including fork and knife, spoons, and others. During the maneuvering, head and trunk may complement the arm movement.

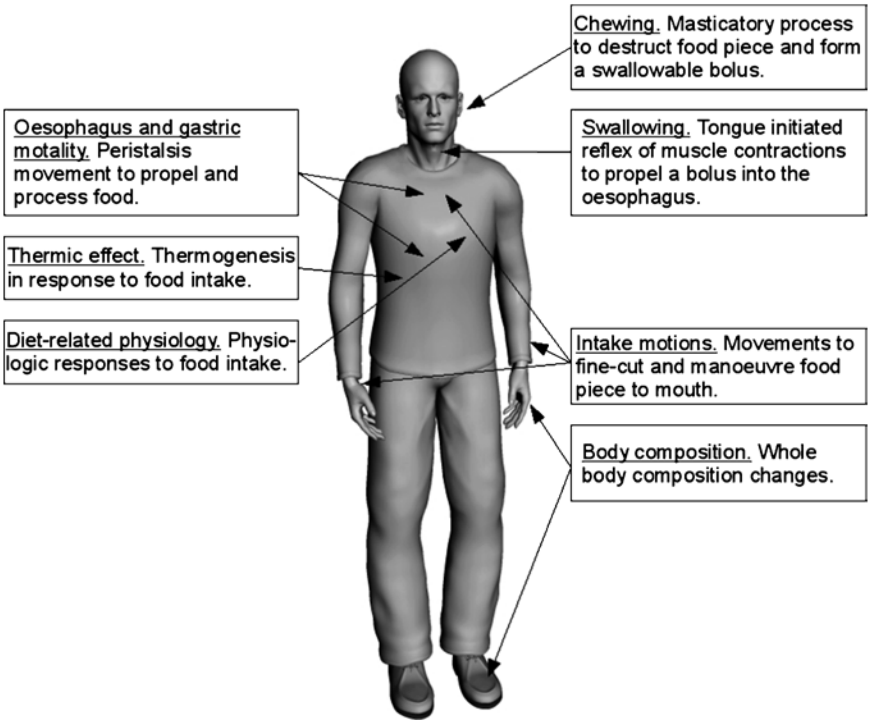

Fig. 219.3 Illustration of on-body and implantable monitoring technologies. Several on-body and implantable monitoring technologies have been investigated to acquire dietary behavior information. The approaches provide different information with regard to the dietary behavior dimensions: intake schedule, eating microstructure, food product/type and preparation, and food amount

By using arm-worn inertial sensors, intake motions can be recognized, which provides information on timing and food type (Amft et al. 2005a; Junker et al. 2008; Amft and Tröster 2008). In particular, intake motions were found to reflect type of intake (eating or drinking) and utensil-specific food category (motion induced by the particular utensils). When studying consumption of four food types, a continuous recognition of intake motions yielded a timing accuracy of ~79% and food classification performance of 94% (Junker et al. 2008; Amft and Tröster 2008). Initial work showed that magnetic position sensors can provide precise posture information between arms and chest. From this data, the orientation of a fluid container and its fill level can be discriminated (Amft et al. 2010). Preliminary results showed an accuracy of 72% for determining three fill levels in nine containers of various shapes and handles. Motion analysis from casual clothing with integrated sensors needs to compensate for sensor–body alignment errors, which requires further research.

Intake motion monitoring is beneficial for detecting dietary activities (intake schedule) and for coarse categorization of the intake type (eating or drinking). Potentially, several food categories can be discerned due to motion pattern differences related to the utensils used (Amft and Tröster 2008).

Chewing: Chewing strokes (jaw opening and closing) during the oral food breakdown can be monitored from masseter and temporalis muscle activations using surface electromyography (EMG) and jaw-attached movement sensors. Because of the measurement in exposed facial regions, these techniques are infeasible for privacy-preserving monitoring in natural environments.

Chewing involves head and hyoid motions as well. Head movement amplitudes were observed to correlate with food piece size and hardness of the bolus (Häggman-Henrikson and Eriksson 2004).

Hyoid motion was frequently observed in EMG recordings at the neck region (Hiiemae et al. 2002). A recent investigation used capacitive sensors to recognize chewing among ten other head–neck movements at ~80% accuracy (Cheng et al. 2010). Chewing motion was recorded by strain gauges at the boom (Sazonov et al. 2008). Dental implants were used to assess load during chewing with strain gauges (Korioth et al. 1997; Stellar and Shrager 1985); however, the approaches can be expected to alter oral sensation and may be infeasible for long-term monitoring. Chewing is moreover reflected in sound and vibrations that propagate through mandible and skull. Chewing can be detected in acoustic data recorded at the ear canal (DeBelie et al. 2003; Amft et al. 2005b). In addition, different food textures can be recognized (Amft et al. 2005b; Amft and Tröster 2009). However, the acoustic structure of chewing sequences is not constant (Amft et al. 2007b). Chewing strokes correlate with food bolus size, and can be used for subject-specific food amount estimation in combination with an acoustic food type recognition (Amft et al. 2009). Ongoing research addresses to compensate for subject-specific properties that hamper chewing recognition performance.

Chewing monitoring provides insight into the eating microstructure, hence to chewing speed, and number of strokes. Chewing monitoring is moreover beneficial to derive meal composition and amount information. The food discrimination from acoustic patterns provides options to identify food categories from their texture structure, including fruits and vegetables, dry and crisp foods, and others.

Swallowing: The swallowing reflex is typically initiated unconsciously by the tongue. It consists of a sequence of throat muscle activations that propel a food bolus through the throat into the esophagus while protecting the trachea (Palmer et al. 1992). Various monitoring approaches concentrate on capturing the swallowing reflex using sensors at the throat. Such sensors can be integrated into collars for long-term monitoring (Amft and Tröster 2009).

The hyoid movement was measured using strain gauges (Honma et al. 2007) and textile strain sensor arrays (Amft and Tröster 2009). While the movement could be captured for males, it is difficult to identify female subjects, due to a less prominent larynx (Danbolt et al. 1999). No relation of movement and bolus size was found (Honma et al. 2007). Pharyngeal muscle contractions using EMG, and the swallowing sound, using the concept of cervical auscultation, have been frequently assessed for diagnosing abnormal swallowing. A review of techniques can be found in Firmin et al. (1997), which covers impedance measurement analyses as well. An artificial palate was developed to assess tongue pressure during swallowing (Ono et al. 2010). EMG was found to be impaired by other throat muscle activations, but sound pattern was influenced by food viscosity and volume (Amft and Tröster 2006). Using collar-integrated capacitive sensors swallowing events were recognized in continuous data with an accuracy of ~80%, while performing head movements (Cheng et al. 2010).

Swallowing can be recognized using various sensor modalities. A combination of the modalities is needed in order to compensate artifacts due to motion, speaking, and chewing in unsupervised settings. Acoustic, EMG, and capacitive modalities are most promising toward a full unobtrusive monitoring system.

Swallowing monitoring is beneficial for obtaining intake schedule, eating microstructure (individual swallows) information, as well as coarse indications of meal composition (viscosity) and food amount.

Thermic effect of food intake: Food ingestion initiates a thermogenesis above the resting metabolic rate. The effect was observed to start immediately after food has reached the stomach and peaks after ~60 min (Westerterp-Plantenga et al. 1990).

For unrestrained, normal-weight individuals, skin temperature above the liver increased due to the thermogenesis between 0.8 and 1.5 K (Westerterp-Plantenga et al. 1990). However, the thermic effect depends on regularity of intake and is lower for irregular intake (Farshchi et al. 2004).

Further investigations are required to determine whether the effect can be utilized to derive dietary behavior information. Because of the delayed pattern, however, temperature measurements of the thermic effect cannot be expected to contribute to immediate intake-related information in a dietary behavior dimension other than intake schedule. Moreover, utilization of the effect in out-of-lab studies will potentially be hampered by uncontrolled physical activities.

Esophagus and gastric motility: After 15 min or less, swallowed food boluses arrive at the stomach through esophagus. Boluses are subsequently decomposed by spontaneous peristaltic movements initiated by muscle contractions. Further digestion in the gastrointestinal tract incurs time delays in the range of hours with respect to the intake moment and thus must be expected to be far less deterministic for immediate intake-related information on any dietary behavior dimension.

Acoustic recordings at the thorax skin revealed xiphoid sounds related to the lower esophageal sphincter operation (Boiron et al. 1999). The sounds could be manually observed for 86% of dry and 94% of wet swallows. Algorithm-based detection rates reached up to 80% (Dellandrea et al. 2003). While muscle contraction analyses have been performed in laboratory settings, e.g., electrogastrography (EGG), these techniques have not reached broad acceptance (Abell and Malagelada 1988). Bowel sounds due to intestinal activity and intake have been initially confirmed (Yamaguchi et al. 2006).

While initial findings exist, further studies are required to confirm the relevance and reproducibility of acoustic monitoring techniques. Electrical or magnetic sensing of gastric peristalsis contractions seem to be limited to stationary setups, thus minimizing body movements. If successful, these effects may not contribute to intake event information due to their delayed and unspecific activations.

Diet-related physiology: Several physiologic responses to food intake have been observed, including increases in heart rate and blood pressure (Valensi and Cosson 2006). The effects are typically delayed, regarding the intake moment and could be masked by physical and mental activations. Thus, no contribution to immediate intake-related information was observed.

Body composition: Food intake modifies body composition, which has been confirmed by bioimpedance spectroscopic measurements. In the laboratory setting, composition alternations were observed 30 min after the intake event (Gualdi-Russo and Toselli 2002). Changes depended on gender and consumed food. With patients in supine position and controlled laboratory setting, malnutrition could be identified at accuracies ranging between 50% and 80% (Wieskotten et al. 2008).

The effect has been investigated under supervised conditions and in supine position primarily. Influences of body motion can be expected to hamper out-of-lab utilization of the effect.

219.5.2.1 Key Features of On-Body and Implantable Monitoring Technologies

1. On-body and implantable monitoring technologies can support autonomous sensing of all dietary behavior dimensions in ADM solutions, thus alleviating respondents from reporting efforts.
2. The technologies can provide detailed eating microstructure information (related to chewing, swallowing, and further intake processing) that are currently not available through ambient ADM techniques.
3. Solutions can be either integrated in clothing, worn on the body (integrated into accessories or directly attached to the skin), or implanted.
4. The techniques provide the option to immediately respond, based on autonomously sensed and processed information and a pre-configured coaching model.
5. On-body and in particular implantable monitoring is exposed to a higher acceptance threshold than questionnaires, due to sensor and processing elements that could be considered as inconvenient.

6. Technologies are constraint in size and require specific considerations regarding wearer comfort, biocompatibility, and impact of long-term use.

A summary of on-body and implantable monitoring technologies is given in Table 219.2.

219.5.3 Approaches in Ambient Monitoring Technologies

Some of the ambient monitoring technologies are illustrated in Fig. 219.4.

Routine monitoring: Food preparation and intake belong to regular daily routines, involving particular subject-specific locations, such as a home dining table or a cafeteria. The rhythm of activities and situations has a repetitive character, which allows deriving behavior models and confirms them from sparse activity sampling using ambient sensors.

Several technical studies investigated this concept. For the coarse preparation and consumption of foods radio-frequency identification (RFID) tags were attached to 60 household objects and a reader was worn at the user's hand to track morning activities (Patterson et al. 2005), including breakfast preparation and consumption. Home activities were identified, including pouring tea, using ambient sound (Negishi and Kawaguchi 2007). Various living-lab studies included additional sensor modalities to study dweller activities (Logan et al. 2007).

Routine monitoring using multimodal sensors in household objects has broad potential to identify dietary behavior information of several dimensions, where intake schedule is the most prominent one. It is conceivable to combine routine monitoring with other ADM-based techniques to address particular monitoring goals. Current research on routine analysis is addressing the fundamental sensor data interpretation and modeling.

Food preparation guidance: Food preparation is a complex household activity, typically involving multiple steps and concurrent workflows. Kitchen recommender systems can support effective food and recipe preparation, minimize hazards, and guide low-fat food composition. Typically, such systems involve multiple sensors to capture food preparation.

A kitchen tray with integrated weight sensors and overhead camera observing the tray content and activity was developed to guide calorie-aware food preparation (Chi et al. 2008). The system could identify individual prescribed foods and preparation steps, and in this way estimate calorie content of the foods. A weight-sensing cutting board and force-sensing knife were deployed to determine food-cutting activities (Kranz et al. 2007). Further kitchen installations used surveillance video, RFID, and magnetic sensors to determine activities (Tenorth et al. 2009).

Food preparation guidance systems are beneficial to analyze meal compositions and complex food preparations involving various ingredients. A combination of these systems with other ADM-based techniques may allow robust assessments of dietary behavior, including the coverage of energy intake and specific biomarkers.

Intake monitoring: Food weighting is used in classic manual assessments to obtain amount information. With the use of plates that integrate a weighting function (load cells), the food amount estimation and elements of the eating microstructure can be assessed without manual reporting. Additional sensor modalities can improve information detail into further dietary behavior dimensions, including a combination with video and RFID. Further smart objects and furniture have been developed to track intake events.

Several studies investigated weighting plates and their benefit in diet coaching programs. Eating rate was controlled using a plate device called Mandometer (Ford et al. 2010). The Mandometer presents the amount and speed of intake during intake events on a feedback screen together with target figures. The results confirm that the device is able to cue and slowdown eating rate in children

Table 219.2 Summary of on-body and implantable monitoring technologies

Monitoring target	Sensing modalities and integration	Addressed dimensions of dietary behaviour
Intake motions Movements to fine-cut and maneuver food piece to mouth	• *Sensors:* inertial sensors, magnetic position sensors • *Integration:* integration into cloths and accessories worn at limbs, trunk, and head feasible	• Intake schedule: ~79% timing accuracy in four intake motion classes.[1,2] Drinking motion: 84%/94% recall/precision[3] • *Composition:* 94% accuracy in four intake classes according to utensils used[1,2] • *Food amount:* during drinking: 72% accuracy for three container fill levels using magnetic position sensors[3]
Chewing Masticatory process to destruct food piece and form a swallowable bolus	• *Sensors:* inertial sensors, capacitive sensors, Electromyography, strain gauge, acoustics, dental implant (strain gauge)• *Integration:* in cloths and accessories worn at neck, ear, and head; dental and oral implants	• *Intake schedule:* up to 90% timing accuracy using in-ear acoustics[1] and ~80% using capacitive collar sensors[4] • *Eating microstructure:* chewing strokes[1] • *Composition:* ~80% accuracy for 19 foods using in-ear acoustics[5] • *Food amount:* 20–30% size prediction error for three foods using acoustics[6]
Swallowing Tongue initiated reflex of muscle contractions to propel a bolus into esophagus	• *Sensors:* Electromyography, sound, strain gauge, textile strain, capacitive sensors, artificial palate (strain gauge) • *Integration:* collar and high-cut shirts, oral implants	• *Intake schedule:* up to ~80% using capacitive sensor array[4] • *Eating microstructure:* swallowing events[4,7] • *Composition:* viscosity at ~75% in two categories using sound[1,7] • *Food amount:* ~74% accuracy in 5 ml and 15 ml water classes using capacitive sensors,[4] ~73% using EMG and sound[7]
Thermic effect Thermogenesis in response to food intake	• *Sensors:* temperature • *Integration:* potentially tight-fitting cloth or (textile) strap	• *Intake schedule:* effect starts ~15 min after food intake and peaks after ~60 min[8] • Relations to composition and amount unknown • Effects may not contribute to intake event information
Oesophagus and gastric motility Peristalsis movement to propel and process food	• *Sensors:* Electromyography, sound, Electrogastrography • *Integration:* no prior data available	• *Intake schedule:* xiphoid sound timing accuracy up to 80%[9] • Composition and amount relations unspecific • Effects may not contribute to intake event information
Diet-related physiology Physiologic responses to food intake	• *Sensors:* heart rate, blood pressure • *Integration:* chest strap or clothing for heart rate	• Timing, composition, and amount relations unspecific • Effects may not contribute to intake event information
Body composition Whole body composition changes	• *Sensors:* bioimpedance when in supine position • *Integration:* hand and foot measurement	• Timing, composition and amount relations unspecific • Effects may not contribute to intake event information • Malnourished patient identification rates up to 80%[10]

The table summarizes approaches in on-body and implantable monitoring technologies, based on Automatic Dietary Monitoring. Key performance figures on individual dimensions of dietary behaviour are presented, together with information on used sensors and integration potential for continuous monitoring in coaching programs

From [1](Amft and Tröster 2008), [2](Junker et al. 2008), [3](Amft et al. 2010), [4](Cheng et al. 2010), [5](Amft and Tröster 2009), [6](Amft et al. 2009), [7](Amft and Tröster 2006), [8](Westerterp-Plantenga et al. 1990), [9](Dellandrea et al. 2003), [10](Wieskotten et al. 2008)

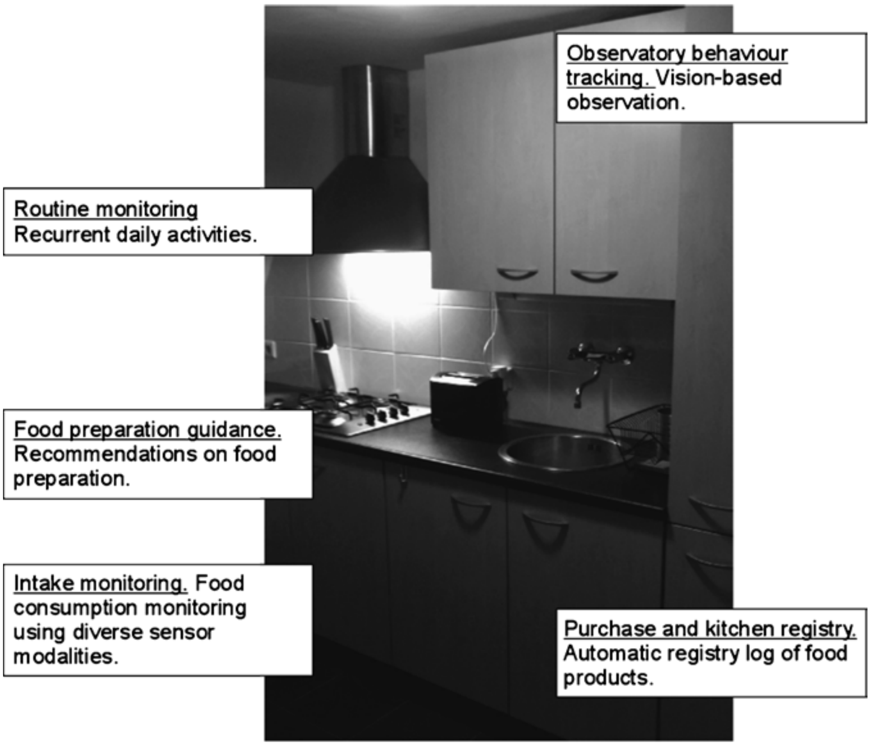

Fig. 219.4 Illustration of ambient monitoring technologies. Several ambient and installed monitoring technologies have been investigated to acquire dietary behavior information. The approaches provide different information with regard to the dietary behavior dimensions: intake schedule, eating microstructure, food product/type and preparation, and food amount

(Ford et al. 2010). A dining table, equipped with weighting sensors for individual sections and RFID to identify several food containers, showed that intake among multiple individuals can be recognized (Chang et al. 2006).

A cup with an embedded motion sensor (acceleration, later ball switch) was used to determine the cup's movement (Beigl et al. 2001). To study and motivate drinking habits in children, a bottle was developed that could monitor fill level from an attached camera (Chiu et al. 2009). A study intervention in 16 subjects showed that the bottle is effective in cueing regular water drinking.

Intake monitoring technologies address all dietary behavior dimensions through integrating monitoring technology in both daily used objects and furniture.

Observatory behavior tracking: Observatory behavior tracking focuses on surveillance video as the primary source of behavioral information.

Similar to the on-body monitoring approach of intake motions, feeding has been investigated using surveillance video (Hauptmann et al. 2004). An algorithm was deployed to identify hands and hand motions toward the head in nursing home patients. Moreover, video observation is an essential tool for food choice analysis (Probst et al. 2009).

Video observation techniques require video cameras to be installed in each section-monitoring environment. Automatic video content analysis algorithms for multi-camera systems require further research. In addition to recognition of activities, the individual person needs to be identified and tracked to correctly assign continuously derived information.

Observatory behavior tracking can in principle address all dietary behavior dimensions. To date, vision analyses had been focused on individual selected scenes and activities.

Purchase and kitchen registry: Food purchases at restaurants and cafeterias can be automatically recorded using traceable payment methods. These systems can be supported by RFID-based product identification. Similarly, kitchen systems, such as refrigerators or smart cabinets, can track their content to recommend meal compositions, provide warnings for foods with limited durability, or support food preparation guidance systems.

Smart cards were used in a study with children to determine food selection and portion size, confirming that the technique is viable for long-term monitoring (Lambert et al. 2005). However, the system was not able to detect that the children exchanged trays and paid for each other. Thus, it is suggested that the technique can only capture food selection, but not actual intake. Similarly, purchased food products could be identified through RFIDs when placed in a refrigerator or cabinet (Juels et al. 2003). Currently, privacy concerns may hamper the practicality of this approach, as RFID tags are destroyed after product sale.

Purchase and kitchen registry systems are beneficial for coarse estimation of intake schedule, since cafeteria purchases are typically linked to consumption, as well as meal composition, and food amount assessments. The extractable information depends on the selected registry technology.

219.5.3.1 Key Features of Ambient Monitoring Technologies

1. Ambient monitoring technologies can support autonomous sensing of all dietary behavior dimensions in ADM solutions, thus alleviating respondents from reporting efforts.
2. Technologies include portable smart objects (e.g. a weighting plate) and build-in installations in dedicated environments, including home (e.g., kitchen, dining table), restaurant, and other setting relevant for dietary behavior.
3. Technologies are mostly limited to one particular environment and smart object.
4. The techniques provide the option to immediately respond, based on autonomously sensed and processed information and a pre-configured coaching model.
5. Specific precautions are required to identify individual user and associate acquired dietary behavior information to this individual.
6. Combinations of ambient monitoring technologies allow to assess food preparation processes, potentially to support calorie and biomarker estimation.

A summary of ambient monitoring technologies is given in Table 219.3.

219.6 Applications to Other Areas

The prospect of monitoring technologies, in particular ADM, will be to serve as decision support for dietitians and coaching support for program participants. ADM can enable long-term assessment of dietary behavior, and as such, provide insight into habitual settings that are currently infeasible. To this end, dietitians, psychologists, and nutrition researchers may adapt diet coaching in the future based on continuous information instead of periodical visits or individually biased self-reports.

In addition, coaching solutions can be assembled that are responsive to the individual user's activities and dietary behavior, effectively forming semi-autonomous dietary assistants. Such solutions are applicable in various opportunities, requiring diet-related coaching and advice, including advising healthy individuals on food preparation and composition, daily dietary routine reminders for the elderly, and behavior change coaching for various diet-related diseases. Systems that leverage this paradigm can support their user with personal in-time diet-related feedback services. The core

Table 219.3 Summary of ambient monitoring technologies

Monitoring target	Sensing approach and integration	Addressed dimensions of dietary behaviour
Routine monitoring Recurrent daily activities	• *Sensors:* RFID, sound • *Integration:* ID tagging of arbitrary objects, RFID reader must be worn.	• *Intake schedule:* up to 88% accuracy in routine detection including 11 steps,[1] single activities from ambient sound 86% accuracy[2] • Relations to composition and amount unknown
Food preparation guidance Recommendations on food preparation	• *Sensors:* RFID, weight sensors, camera, force sensors, magnetic sensors • *Integration:* in kitchen tray, kitchen utensils, kitchen furniture	• *Intake schedule:* not applicable • *Composition:* recognition of preparation steps at up to 92% accuracy[3] • *Food amount:* not evaluated
Intake monitoring Food consumption monitoring using diverse sensor modalities	• *Sensors:* RFID, weight sensors, camera • *Integration:* in dining table, weight sensors in plate (Mandometer)	• *Intake schedule:* not specifically addressed • *Eating microstructure:* weighting tables, weighting plate • *Composition:* up to 80% accuracy in identifying food containers[4] • *Food amount:* weighting tables, weighting plate; camera bottle achieved average estimation errors of ~3.8%[5]
Observatory behavior tracking Vision-based observation	• *Sensors:* surveillance video • *Integration:* typically at ceiling of individual rooms or areas	• *Intake schedule:* ~80% timing accuracy[6] • Relations to composition and amount unknown
Purchase and kitchen registry Automatic registry log of food products	• *Sensors*: smart card, RFID • *Integration*: registry, refrigerator, kitchen cabinets	• *Intake schedule*: coarse estimation due to link of purchase and consumption • *Composition:* detailed information from product codes or RFID[7] • Food amount: from registry information[7]

The table summarizes approaches in ambient monitoring technologies, based on Automatic Dietary Monitoring. Key performance figures on individual dimensions of dietary behavior are presented, together with information on used sensors and integration potential for continuous monitoring in coaching programs

RFID radio-frequency identification

From [1](Patterson et al. 2005), [2](Negishi and Kawaguchi 2007), [3](Chi et al. 2008), [4](Chang et al. 2006; Ford et al. 2010), [5](Chiu et al. 2009), [6](Hauptmann et al. 2004), [7](Lambert et al. 2005) functions for such personal dietary assistants are (1) sensing and autonomously recognizing the user's state and dietary behavior, (2) inferring health and diet state as well as tracking tasks and actions relevant for the targeted service, and (3) providing adequate feedback and coaching based on a pre-configured and periodically updated coaching model.

219.7 Future Trends

Research on monitoring technologies will further address computer-based manual and ADM-based assessments. It can be expected that ADM-based solutions will initially address specific diet tasks, such as monitoring fluid intake in the elderly. Furthermore, solutions will become configurable and adaptive to the actual monitoring needs. Thus, dietitians can customize solutions for their patients.

Eventually ADM concepts will become an integrated part in coaching solutions and tailored to the individual user, regarding monitoring and personal development goals.

Summary Points

- Dietary behavior can be categorized according to the dimensions: intake schedule, eating microstructure, food composition and preparation, and consumed food amount.
- When categorizing dietary monitoring technologies, most prominent classes are manual and automatic assessments; classic paper- and computer-based monitoring (manual assessments); on-body/implantable and ambient/installed sensor-based monitoring solutions (automatic assessments).
- Monitoring detail and resolution are determined by the particular information sampling techniques used: assessments capturing individual intake events can acquire behavior information immediately at the event, whereas frequency assessments aim to derive dietary behavior history over a period of several weeks and months.
- Automatic Dietary Monitoring (ADM) summarizes approaches to replace paper- and computer-based manual monitoring with autonomous sensor-based monitoring of at least one dietary behavior dimension. It targets to alleviate the respondent's effort, while providing more information details and higher information quality compared to manual techniques.
- ADM is best utilized by configuring monitoring modules according to the analysis goals. For the addressed situation and user group, e.g., preventing dehydration in geriatric patients, a specific set of ADM modules will be utilized.
- On-body and implantable ADM refers to sensor-based monitoring techniques that can be integrated into clothing (wearable), attached to the body, or implanted into the body. The techniques provide detailed eating microstructure information and solutions that are not location-dependent.
- Ambient ADM refers to sensor-based monitoring techniques that can be embedded into dining-related environments and objects. The techniques can provide information on all dietary behavior dimensions.
- A combination of ADM and computer-based manual monitoring can be most efficient for initial implementations of ADM in diet monitoring studies. The combination could allow to reduce respondent effort while compensating insufficient performance of ADM module prototypes.
- Individual ADM modules are limited in the number of dietary behavior dimensions that they can capture, due to the complexity of natural daily life and dieting habits. A combination of ambient and on-body ADM could be most efficient to cover daily routines in out-of-lab monitoring entirely.

Definition and Explanation of Key Terms

Dietary behavior: Summation of all habitual choices of an individual when selecting and consuming food. Different dimensions of dietary behavior can be identified (see main text) to describe particular monitoring needs.

Eating microstructure: Interaction of licks, chewing, oral bolus formation, tongue activity, and swallowing.

Inertial sensors: Class of sensors that includes acceleration, earth magnetic field (compass), and gyroscope (rate of turn) sensor modalities. Typically, each modality is measured in three dimensions.

Thermogenesis: Immediate increase in metabolic rate above the resting rate in response to food intake. It results in the thermic effect of food intake (temperature increase).

Swallowing reflex: Sequence of pharyngeal muscle activations when initiated by the tongue. The reflex aims to propel a food bolus into the esophagus, while preventing trachea contamination.

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