Monitor Pilgrims: Prayer Activity Recognition using Wearable Sensors

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ABSTRACT

Each year, millions of Muslims visit the holy sites in Makkah and Madinah. The so-called Hajj pilgrimage is one of the biggest annual events in the world. The individual impact on participating pilgrims is significant, with many of the pilgrims reporting it as a life-changing event. However, quite a little is done to objectively monitor the pilgrims and to understand, from the individual point of view, the characteristics of each of the pilgrimage stages. In this work, through observing differences in bio-physiological responses of the subjects during prayers, we are able to differentiate, in the first case, between congregational prayers and individual prayers, and, in the second case, between silent prayers and loud prayers. We collected data from 10 participants in an 8-day pilgrimage using two wearable sensors, namely chest belts and wrist-worn devices. We derive features from ECG, respiration and GSR data, and use the ANOVA model to analyze feature groups. Based on that, we build classifiers to differentiate between types of prayers. The SVM classifier shows the best performance with a mean accuracy rate of 78 % for the first case, and 84 % for the second case.

Categories and Subject Descriptors

H.4 [**Information Systems Applications**]: Miscellaneous

General Terms

Algorithms, Measurement, Experimentation

Keywords

Wearable sensors, pilgrims, prayer, HRV, GSR, respiratory

1. INTRODUCTION AND MOTIVATION

Pilgrimage is a journey in search of spiritual relief. It is important for people of many different religions. Recent statistics show that the total number of people participating in pilgrimages, of all religious faiths, is growing [1].

BODYNETS 2013, September 30-October 02, Boston, United States

DOI 10.4108/icst.bodynets.2013.253685

The annual pilgrimage for Muslims is called Hajj. It is a very old event with the rituals dating back to as early as the time of prophet Abraham. Islam requires every adult who fulfills health and financial conditions to perform the pilgrimage at least once in his or her lifetime. During this pilgrimage, millions of people from all over the world congregate for religious rituals in the holy sites in the city of Makkah and around the city. Visits to the city of Madinah, although voluntary, are very common. Umrah, also known as the ”lesser pilgrimage”, is the visit to the sacred sites outside the period of Hajj (for details see, e.g., [3]).
Using two wearable sensors, we collected data from bio-physiological responses of people performing different types of prayers during an Umrah pilgrimage. Thereof we extract a large number of features from electrocardiography (ECG) and heart rate variability (HRV), respiratory (Rsp), and galvanic skin response (GSR), and then using the ANOVA model, we determine groups of features relevant to discriminating, in the first case, between congregational and individual prayers, and, in the second case, between silent and loud prayers. At the end, we compare several state-of-the-art classifiers in order to find out the one with the highest predicting accuracy for each of the two two-class cases.

The long-term goal of our project is to determine the characteristics of each complex stage of pilgrimage, then to observe the health, stress and emotional state of the pilgrims through each of these stages, and finally to understand the interrelation between these two. The motivation behind this is to better understand the experience of the pilgrims and then to offer help where necessary. The daily prayers are the most commonly occurring ritual in Hajj. With this in mind, they present a suitable platform in which to investigate the changes in the bio-physiological responses of the subjects, in an environment with stimuli such as the participation in an ordered, congregational ritual, and the loud recitation of the prayer supplications. Having detected these response changes during prayers, we think that we can move onto the investigation of the other stages of the pilgrimage in a similar approach, as we belief that each stage presents a unique set of stimuli and effects on the subjects.

Nowadays, the emerging technologies of wearable devices allow an enriched and deepened dimension of data analysis. The devices are mobile, unobtrusive and are equipped with physical as well as bio-physiological sensors. In our study, the participants wear commercially-available chest belt sensors and wrist-worn devices during an Umrah pilgrimage.

The paper is organized as follows: In the next section, related work is presented. Then, we describe the study design, the data collection and the sensors used. The recognition of prayer types is discussed in section 4, showing the methods, the outcomes and the limitations. The work is concluded by summarizing the main achieved results and by showing possible improvements and extensions.

2. RELATED WORK

There are several studies done on tracking and monitoring pilgrims using smartphone devices. Most of them focus on designing systems for identifying pilgrims in case they get lost or cannot find the way out of the massive crowds. In [6] and [9], the authors describe two frameworks that provide pilgrim tracking using smartphones. Their main goal is to improve the transportation infrastructure and crowd management services for Hajj and Umrah. HajjDoc [4] aims at efficient collection of geo-tagged data, such as images, videos and audio recordings, through smartphones distributed to pilgrims. These data serve as input for creating an enriched documentation of the Hajj and Umrah pilgrimages. To the best of our knowledge, there is no research contribution in our area of interest yet, and especially no study using any kind of wearable sensors.

However, similar works using wearable devices have been carried out in areas different than pilgrimage. There is an emerging, more general research on detecting stress and mental workload using wearable devices, mainly based on two biosensors: GSR and HRV. In [5], GSR is used to detect stress in call centers and in [7], students under stress due to university examinations are investigated using HRV measures. However, in these and other studies, a strong stimulus that invokes stress is presented to the subjects. The Affectiva Q sensor [11] is a commonly used sensor for measuring emotions or stress, based on GSR. This sensor, developed in the Affective Computing Lab [8], is very similar to the wrist-worn sensor used in our study.

The contribution of our work for the current research is that, firstly, we combine two different wearable devices to investigate changes in bio-physiological response and, secondly, we apply the analysis on a novel topic which is prayer activity during pilgrimage.

3. DATA COLLECTION

In this section, we briefly describe the data collection. More information can be found in our previous work in [10].

3.1 Participants and Wearable Devices

The Umrah trip lasted 8 days, with 10 pilgrims participated in the data collection. The oldest and the youngest subjects were 21 and 53 years old, respectively. Mean and standard deviation were 34 and 11 years. Two different wearable devices were used: the chest strap Zephyr Bioharness 3 [13] and the wristband Empatica E2 [2] (see Figure 1). All participants participated voluntarily and signed a written informed consent. Table 1 lists the built-in sensors in both devices.

3.2 Sensing Schedule and Prayer Annotation

There was no sharply-defined sensing schedule. As a general rule, participants were encouraged to wear the devices preferably the whole day, but at least while performing the 5 daily prayers. Data recording is triggered by pressing a button. Three of the participants marked the start and stop

Figure 1: Zephyr BioHarness 3 and Empatica E2

Zephyr BioHarness 3	Empatica E2
Heart Rate [1/min]	Pulse [1/min]
Breathing Rate [1/min]	GSR (@ 4 Hz)
ECG (@ 250 Hz)	3D acceleration (@ 100 Hz)
Posture (±180°)	Skin temperature (@ 2 Hz)
Activity level {S, W, R}	
3D acceleration (@ 100 Hz)	

Table 1: Wearable Sensor Modalities

timestamps of the prayer events individually. The final labels were computed by averaging the individual annotations.

Data were copied from the sensing devices every other day, on average. The clocks of wearable sensors were synchronized during connection to the computer.

4. PRAYER TYPE RECOGNITION

4.1 Definition of Prayer Activity

One prayer unit may have 2, 3, or 4 sections, e.g., the morning prayer has 2 sections, and the evening prayer 3 sections. One section itself consists of 6 stages: 1. long standing, 2. bowing, 3. short standing, 4. first prostration, 5. sitting, and 6. second prostration. Figure 2 shows one full prayer section with the 6 stages.

The segmentation and the annotation of the stages of the prayer are done manually. To do that, we first zoom-in into the labeled daily prayers. Within these prayers we define the starting and ending timestamps of each segment by visual inspection using the acceleration signal of the wrist-worn Empatica device and the acceleration and posture curves of the Zephyr device. Arms and upper-body movements and positions are a reliable indicator of the stage transitions.

4.2 Classification Procedure

We consider two cases, and in each case the aim is to differentiate between 2 types of prayers:

- Case 1: congregational prayers vs individual prayers
- Case 2: loud prayers vs silent prayers

The classification is only based on the first stage (long standing) of a prayer section. The person is standing still, and we assume that the physical activity during this period (t_0+5% to t_1-5%) is very small and can be neglected. Additionally, the duration of the first stage is long enough for the emotional reactions to the external effects to take place.

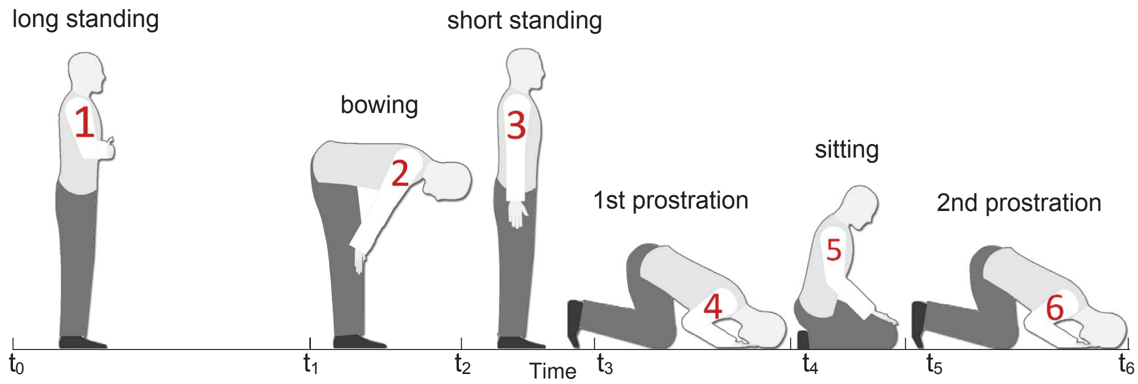

Figure 2: An illustration of one full prayer section with 6 stages

We extract HRV/ECG, Rsp, and GSR features using the Augsburg Biosignal Toolbox (AuBT) [12]. Table 2 shows groups of features within each modality.

HRV/ECG	Rsp	GSR
Time	Pulse	Statistical
Nonlinear	Amplitude	1. Derivation
Frequency	Spectrum	2. Derivation
89 Features	67 Features	22 Features

Table 2: Groups and Number of Features

Next, we use the analysis of variance (ANOVA) to find out for each feature whether its values differ significantly between two classes. With the ANOVA test we aim at finding groups of important features for each sensor modality.

Then, the high number of features (178) will be reduced to the most significant ones. The ANOVA test alone is not enough, since, for instance, two significant features might have a high correlation. To overcome this, the sequential forward selection (SFS) is applied to the features which are ordered by their significance.

Finally, the selected features are used to train person-independent, i.e., general, classification models. For training and testing the models, we apply the 10-fold cross validation from a total of 382 prayers.

We show the performance of the following classifiers to discriminate the two classes within each case: support vector machine (SVM), logistic regression (Logit), k-nearest-neighbor (kNN), and random forest (RF).

Modality	Case 1	Case 2
ECG	52	21
Rsp	23	13
GSR	4	12
Total	79 Features	46 Features

Table 3: Number of significant features for each modality and each case

4.3 Results

Table 3 shows the results of the ANOVA test. 44 % of the features for Case 1 and 26 % for Case 2 pass the significance test (significance level $p < 0.05$). We can notice that these features are spread across all sensor modalities for both cases. Tables 4 and 5 show an exemplary list of significant features with the corresponding p and F values.

Modality	Features	p; F
HRV/ECG	std HRV	0.017; 39.12
	SD1/SD2	0.007; 1.146
Rsp	mean Rsp	0.012; 509.4
	std Rsp	0.000; 22.74
GSR	max 1.Diff	0.004; 0.429
	max 2.Diff	0.006; 0.649

Table 4: A list of significant features for Case 1

Modality	Features	p; F
HRV/ECG	LF/HF	0.015; 0.822
	HRV index	0.000; 1744
Rsp	std Ampl	0.033; 256.6
	median Pulse	0.012; 696.9
GSR	median GSR	0.028; 2585
	ratio GSR	0.018; 2.527

Table 5: A list of significant features for Case 2

SFS reduces the number of important features from 178 to 10, on average, where most of them are from the ECG/HRV and Rsp modalities. This high reduction indicates that the features seen as significant by the ANOVA test are correlated. From the HRV/ECG feature group, only HRV features remain in the subset. This has a positive practical consequence, since the ECG waveform, which is much more difficult to get than only the HRV signal, can be neglected for future studies.

Using the 10 resulting features, the classifiers perform as depicted in Figure 3. The SVM classifier achieves the best accuracy for both cases, 78 % for Case 1 and 84 % for Case 2.

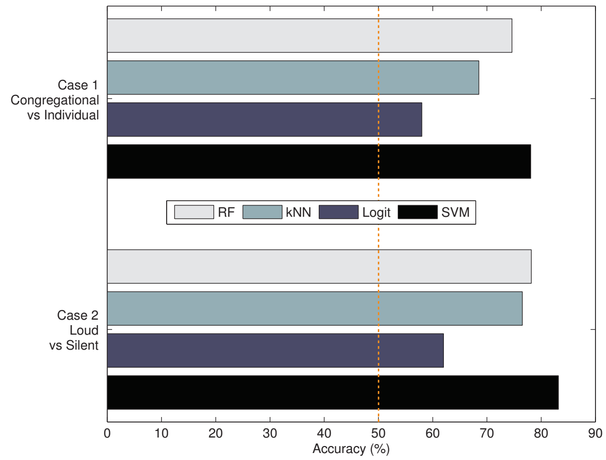

Figure 3: The prayer recognition accuracy of SVM, Logit, kNN and RF classifiers for Cases 1 and 2

Logit on the other side has the lowest performance with an accuracy of slightly above the baseline. The differentiation between silent and loud prayers seems to be the easier task, in general.

4.4 Limitations

We directly use the selected features to build the models without trying to interpret them beforehand. Moreover, this feature set should be compared with features used in the area of emotion recognition, and similar topics.

SFS is combined with SVM as a wrapper for the feature selection approach. This combination favours the SVM classifier. A better approach would be to combine SFS with all classifiers separately, and have a set of selected features per classifier.

The bio-physiological response might not only be caused by the prayer type itself, other influences, such as the temperature or the day time, should also be taken into account.

5. CONCLUSION AND ONGOING WORK

In this work, we have shown that it is possible to detect changes in bio-physiological response of pilgrims when different types of prayers are performed.

We briefly described the data collection conducted in the cities of Makkah and Madinah and explained the wearable sensors used for the study.

Then, using the ANOVA model, we identified a list of significant features, which was then reduced to a set with the most important ones, using the SFS method for feature selection.

We built different user-independent classifiers and assessed the prediction accuracy using cross-validation.

The best performance was achieved by the SVM classifier, which was able to differentiate between congregational and individual prayers with an accuracy of 78 % and between loud and silent prayers with 84 %.

The presented work provides a basis toward accomplishing our long-term objective for recognizing health, stress and emotional states of the pilgrims during all pilgrimage stages.

During the Umrah data collection, we also distributed Android smartphones to 41 pilgrims. The smartphones were configured to capture proximity information, audio features, acceleration of the device, and location of users. These data will be used for social network analysis during pilgrimage.

The upcoming Hajj pilgrimage in October 2013 offers the next opportunity to extend and further evaluate our work.

6. ACKNOWLEDGMEMENTS

The authors would like to thank Zephyr Technology Corp. and Empatica S.r.l for providing the wearable sensors, then Enis Abdyli for valuable inputs, and the pilgrims participating in the study.

7. REFERENCES

[1] Alliance of Religions and Conservation (ARC). Pilgrim numbers. `http://www.arcworld.org/projects.asp?projectID=500`. Accessed May 2013.

[2] Empatica. E2. `https://www.empatica.com`. Accessed May 2013.

[3] F.E. Peters. *The Hajj: The Muslim Pilgrimage to Mecca and the Holy Places*. Princeton University Press, 1994.

[4] HajjDoc. Pilgrims-Sourced Data Collection for Documentation and Continous Improvement of Hajj and Umrah. `www.hajjdoc.net`. Accessed May 2013.

[5] J. Hernandez, R. R. Morris, and R. W. Picard. Call center stress recognition with person-specific models. In *Int. Conf. on Affective Computing and Intelligent Interaction (ACII)*, 2011.

[6] T. Mantoro, A. Jaafar, M. Aris, and M. Ayu. Hajjlocator: A hajj pilgrimage tracking framework in crowded ubiquitous environment. In *Int. Conf. on Multimedia Computing and Systems (ICMCS)*, 2011.

[7] P. Melillo, M. Bracale, and L. Pecchia. Nonlinear heart rate variability features for real-life stress detection. case study: students under stress due to university examination. *Biomed Eng Online*, 10(1):96, 2011.

[8] MIT Media Lab. Affective computing laboratory. `http://affect.media.mit.edu/`. Accessed May 2013.

[9] M. Mohandes. Pilgrim tracking and identification using the mobile phone. In *IEEE Int. Symposium on Consumer Electronics (ISCE)*, 2011.

[10] A. Muaremi, J. Seiter, A. Bexheti, and G. Tröster. Monitor and understand pilgrims: Data collection using smartphones and wearable devices. In *Int. Workshop on Human Activity Sensing Corpus and its Application (HASCA)*, 2013.

[11] M.-Z. Poh, N. C. Swenson, and R. W. Picard. A wearable sensor for unobtrusive, long-term assessment of electrodermal activity. In *IEEE Int. Conf. on Eng. Med. Biol. Soc. (EMBC)*, 2010.

[12] J. Wagner, J. Kim, and E. Andre. From physiological signals to emotions: Implementing and comparing selected methods for feature extraction and classification. In *IEEE Int. Conf. on Multimedia and Expo (ICME)*, 2005.

[13] Zephyr. Bioharness 3. `www.zephyranywhere.com`. Accessed May 2013.