eRing: Multiple Finger Gesture Recognition with one Ring Using an Electric Field

Mathias Wilhelm, Daniel Krakowczyk, Frank Trollmann, Sahin Albayrak
DAI-Labor, Berlin Institute of Technology
Ernst-Reuter-Platz 7, 10587 Berlin, Germany
{firstname.surname}@dai-labor.de

ABSTRACT
Since gestures are one of the natural interaction modalities between humans they also represent a promising interaction modality for human computer interaction. Finger rings provide an unobtrusive way to detect hand and finger gestures if they are able to detect a large variety of gestures involving hands and multiple fingers. One method that could be used to detect such gestures with a single ring is electric field sensing. In this paper we present an early prototype, called eRing, which uses this method and evaluate its capability to detect different finger- and hand-gestures via user study.

Author Keywords
Ubiquitous Interaction Device; Gesture Recognition; Finger Gesture Recognition; Finger Ring; Electric Field Sensing; Capacitive Sensing

ACM Classification Keywords
H.5.2. Input devices and strategies

INTRODUCTION

Gestures are one of the natural interaction modalities between humans. This has also been recognized by the field of human computer interaction where more and more gesture interaction approaches are developed (e.g. [15]). Unfortunately, different domains, devices, and services currently provide different means of detecting gestures. A single interaction device that is available throughout the daily routine would be more natural for a user. A gesture recognition approach that is applicable in this way has to fulfill the following requirements:

- Ubiquity: The gesture recognition should be independent of location, time and other external factors, e.g. illumination, and a long battery life time requires low-power consuming hardware.
- Unobtrusiveness: The gesture recognition should not obstruct the user in her daily routine or draw unwanted attention [12].
- Richness of interaction set: The gesture recognition should be able to detect a large set of different gestures.

In this paper we present the idea of a finger ring, equipped with an electric field to detect hand and finger gestures evaluate it with regards to the above mentioned requirements. We first consider related work for the detection of these types of gestures and derive that a detection mechanism for multiple finger gestures based on a single finger ring would be a good basis for a ubiquitous and unobtrusive gesture recognition approach. Afterwards, we discuss briefly the technique of electric field sensing and describe a prototype implementation. This prototype is then evaluated with regards to its capability to detect different gestures. Finally, we discuss the implications of our tests with regards to the fulfillment of the above requirements and conclude the paper.

Related Work

Extensive research in the field of gesture recognition over the past decades led to numerous gesture recognition algorithms and dedicated devices [15]. In this section we analyze existing wearable gesture devices and their potential for a ubiquitous gesture interaction device. We classify these devices into four major groups: camera-based interfaces, sensor gloves, wrist bands, and finger rings.

Camera-based gesture interfaces [1, 13, 16, 17] allow users to gesture in a natural and intuitive way. As a result of extensive research, camera-based gesture interfaces can enable precise tracking and high recognition performance. In context of ubiquitous computing, there are three major drawbacks of these interfaces: occlusion, illumination sensitivity, and a limited field of view (in dependence of the mounting position). In case of a head or body mounted camera for example, the user must bring his limbs into the active field of view of the camera, which is in the front of the user's body in this case. This can be exhausting for the user and it does not allow performing unobtrusive gestures, such as micro gestures. Further, such interaction needs some space in front of the user's body which could make it difficult to gesture, for example in an over-crowded bus. This style of interaction can also let some users feel strange

WOAR '15, June 25 - 26, 2015, Rostock, Germany

DOI: http://dx.doi.org/10.1145/2790044.2790047

and awkward by performing obtrusive gestures in public. In contrast, wrist or arm mounted camera solutions allow also to perform unobtrusive finger gestures, but they have to deal with occlusion by jackets, gloves, or other clothes. In spite of this, all camera-based approaches have to deal with changing illumination conditions, such as strong direct sunlight or any absence of light.

Like camera-based gesture interfaces, sensor gloves [5] provide almost the same advantages. In context of everywhere and every time interaction, sensor gloves suffer in tactile feedback and in comfort because users must wear them everywhere and all the day. This is uncomfortable in summer or in wet conditions such as sports for example. Similar to camera-based devices, they draw attention in public (for example in summer or indoor).

The strength of wrist band-based gesture devices [4, 14, 18] is that they are small and unobtrusive. In combination with motion sensors, they are able to detect a wide spectrum of hand and finger gestures. On the other hand, they can only detect broad gestures and no subtle finger movements.

Although equipped with plenty of sensors and electronics, finger rings can be designed with a small and unobtrusive form factor [7, 10, 12]. They allow the tracking of small and sensitive micro gestures which can be performed without attracting much attention and even without interrupting the current task. In contrast to the other interaction devices above, they suffer obviously in the variety of possible gestures. Unless multiple fingers are equipped with a ring [9], which would reduce the comfort and unobtrusive factors, only the posture and the movement of one finger (usually of the index finger) can be detected and tracked. Considering a finger ring with the power to track the posture and gesture of at least the neighboring fingers, such a ring would combine all advantages of the gesture devices above.

ERING

In difference to traditional finger ring solutions making use of motion and touch sensors, eRing applies an electric field around the ring and measures the changes of the electric field caused by the other fingers and the hand itself (Figure 1). This enables recognition and tracking of multiple finger postures and gestures via one finger ring. In this paper, we focus on the description of a first prototype utilizing only the electric field to show the general feasibility of our idea.

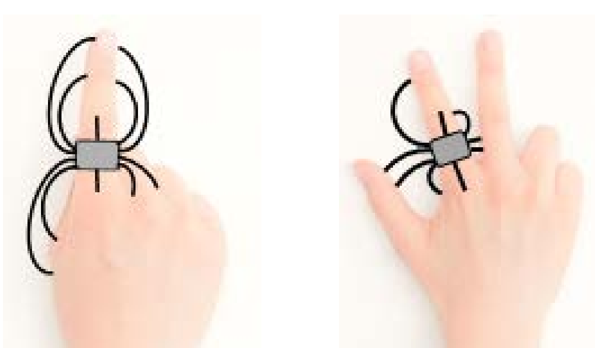


Figure 1. Visualization of the eRing idea.

Electric Field Sensing

Electric fields are omnipresent and act on electric charges, while capacitance is the ability to store this charge. Typically a capacitor is presented as a parallel pair of two metal plate electrodes which constitute an electric field. For electric field sensing, one electrode that builds up a capacitor with its dielectric environment is sufficient. In the case of a nearby moving conductive object the capacitance changes as a consequence. This variable capacitance is therefore a well-fitting way of measuring the proximity of the conductive human skin and is widely used as a noncontact touch and proximity sensor [2].

There are varying ways of measuring this capacitance, the most popular being frequency modulation, e.g., used by Lev Sergeevič Termen for creating one of the first electrical music instruments: the Theremin. By increasing the variable capacitance the resonant frequency decreases. There also exist additional modes in which an electrode can either be configured as a transmitter or receiver [8, 19].

For our first prototype a simpler alternative has been chosen. With an additional resistor a RC circuit is build (Figure 2). In this operation mode the changes of the surrounding electric field are sensed by measuring the charging time of the electrode. Setting the send pin to a high value will have a measurable delay on the receive pin due to the charging of the capacitor. This rise time τ is proportional to the product of resistance and capacitance, which enables the inference of the sought capacity C_x.

Apart from the capacitor electrode the only explicit component is thus the resistor. Low values will result in shorter charging times, while high values will result in a more sensitive response. Hence there's a tradeoff between response time and resolution.

Prototype Implementation

The constructed prototype (Figure 3) consists of four components. A 3D printed finger ring provides the body to attach the sensor system. Four copper foils are attached to the ring's lower sides and act as distinctive electrodes for capacitive sensing. To prevent direct contact between skin and electrode, adhesive tape is used as an isolator. A small board with just four 10 MΩ resistors is mounted on top of the ring and serves as the driving circuit for the capacitive measurement. Sitting on its top, an Arduino Nano sends

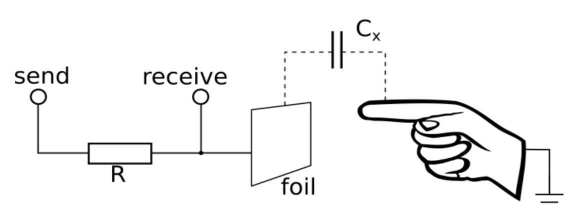


Figure 2. Circuit for a single electrode of eRing.

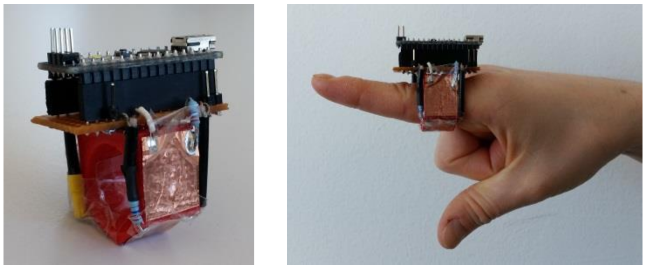


Figure 3. eRing prototype.

step inputs and measures the respective time delay by utilizing the open source CapSense library written by Paul Badger [3]. The Arduino is connected via USB to a PC for processing and classification. Due to its minimal design the system consumes a total power of maximum 0.2 Watt. The consumption is almost entirely determined by the microcontroller. The sensor driving board consumes 10μW.

Gesture Recognition

In order to classify gestures in the four dimensional sensor data, we use a 1-nearest neighbor (1NN) classifier with lucky time warping (LTW) [20] as a similarity measure. It has been shown that the 1NN classifier is a good choice for time series classification [21], such as gesture recognition. Additionally, it is parameter-free, requires only a small number of training examples, provides easy to comprehend results, and has in connection with LTW a linear time and space complexity. This allows the implementation of the classifier on small microcontrollers.

Since we obtain a four-dimensional time series from the ring, we have to replace the one-dimensional distance function $d(q_i, c_i)$ in [20, Eq. 7] with:

$$d(q_i, c_j) = \sum_{d=1}^{D=4} (q_{i,d} - c_{j,d})^2, \quad (1)$$

where $q_{i,d}$ is the d^{th}dimension in i^{th}data point in the time series Q, $c_{j,d}$ is the d^{th} dimension in j^{th}data point in the time series C, and D is the number of dimensions.

For the prototype presented in this paper, we introduce two classifiers: one for static finger postures and one for dynamic finger gestures. The difference between both is the preprocessing step of the time series. For the dynamic finger gestures, we apply the *z*-score normalization:

$$Q_z = \frac{Q - \mu(Q)}{\sigma(Q)}, \quad (2)$$

where Q is a times series to be normalized, $\mu(Q)$ is the mean of Q, $\sigma(Q)$ is the standard deviation of Q, and Q_z is the normalized time series. This normalization is important because the amplitudes of one gesture class can have strong variations. These variations have a big influence on the similarity measure and can lead to false classifications [11].

In contrast to static finger postures, there is no time varying pattern but different constant amplitudes. A *z*-score

d	**0**	**4**	**7**	**10**	**14**	**17**
μ	1.5365	1.43	1.4089	1.3954	1.3918	1.39
σ	411	140	79	27	13	6
μ_f	1.6801	1.5420	1.5134	1.5046	1.4996	1.4980
σ_f	876	190	79	32	14	8

Table 1. Mean μ and standard deviation σ values of the 20 runs for sensor 1 over different distances d in approximated millimeter. The index *f* indicates the signal, which was recorded with the ring worn on the finger.

normalization would eliminate the distinguishability of different posture classes, because after the normalization the posture data is close to the zero-baseline. Accordingly, for dynamic finger gesture recognition we apply the *z*-score normalization before we classify the gesture with the 1NN classifier and the recognition of static finger gesture is based on the raw sensor data for the 1NN classification.

EVALUATION

In order to show the general feasibility of our idea of an electric field-based ubiquitous gesture device and evaluate our prototype, we conducted three experiments. In the first experiment we explored the range of the electric field and the sensitivity. Based on these results, we defined six postures and six dynamic gestures to test the recognition capabilities of the prototype. These gesture sets were separately evaluated in two experiments.

To make our experiments as comprehensible and transparent to the community, we published all scripts and data used in this paper in an online code repository [6]. For interested readers the repository also provides some additional experiments and their results, which are out of scope of this paper or skipped due to space limitations.

Experiment 1 – Sensitivity and Field Range Test

First, we studied the field range and sensitivity of our prototype. For this, we used a WACOM pen tablet[1] and pen to measure the ranges. The ring was fixed on the tablet. The pen was held between thumb and the index finger of the left hand. The index finger was placed at the ring, so that it touched one electrode, and it was moved 2cm away from the electrode along a ruler fixed on the tablet while recording the sensed values of the electrode and the position of the pen. This procedure was repeated 20 times for each electrode. To simulate the influence of a finger inside the ring, we put the ring on the right hand index finger and performed the same procedure as before. The results from this experiment did not deviate from the first experiment and are thus omitted from this paper. The sensor values, the moved distances in pixel (2cm equals about 90 pixel), and the time line were written in a file.

[1] WACOM Intous®3 Graphics Tablet PTZ-1230

Afterwards, we computed the mean and standard deviation of the 20 runs for each sensor.

Results

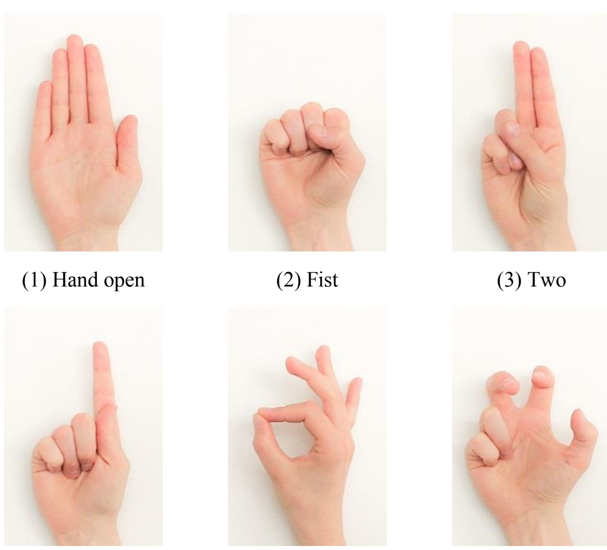
The experiment revealed that the average field range is about 1cm. The values increase only slightly for distances bigger than about 5mm. For smaller distances clear signal changes can be observed. However, with decreasing distance, the standard deviation increases rapidly. Table 1 shows this relationship for sensor 1. It reveals also that the standard deviation increases and the field range decreases, if the ring is worn on the index finger.

Discussion

This experiment shows that the electric field of our prototype is small. For this reason, only the tracking of neighboring fingers is realistic. Since the effective field range is only about 5mm, the neighboring finger should be close to the ring.

Experiment 2 – Finger Posture Recognition

In a second experiment, we aim to show the feasibility of detecting finger postures with eRing. Based on the results of experiment 1, we defined six postures involving the thumb, the index finger, and the middle finger (Figure 4). Due to the limited range of the prototype we chose gestures that can be distinguished based on the position and distance of thumb and middle finger if the ring is placed on the index finger (cf. Figure 3). We gathered 50 examples for each posture in one session from one of the authors. In total we collected 300 posture examples. For this process, we used an evaluation software, which asked the participant to perform a certain posture. The sequence of postures to perform was random and no posture was chosen in sequence. In order to be able to segment properly the postures for the offline classification, the participant labeled the postures with a button installed with a wire on eRing.



(1) Hand open (2) Fist (3) Two

(4) Pointing (5) Ring (6) Grasp

Figure 4. Finger postures used in experiment 2.

Every time he moved his finger in the requested position, he pressed the button for at least one second. The four dimensional sensor data, the time line, the requested labels and the button state were written in a file.

After the recording, we extracted the labeled postures with a script and stored them in a suitable data structure. In order to decrease the influence of the selected training examples and to provide reproducible results, we performed cross-validation. We split the data set into 10 sequential partitions. Each partition contained 30 training examples. These are 5 examples for each posture, which fits a practical size for online gesture recognition. We took one partition as the training set and the remaining nine were used as test set. This procedure was repeated for each of the 10 partitions. For the classification of the postures, the raw sensor data and a 1NN classifier with LTW as similarity measure was used.

Results

The mean error rate of the 10 runs in experiment 2 was 0.027. Figure 5 contains the confusion matrix of the experiments where we can identify which postures were miss-classified. The columns represent the posture classes and the rows represent the class as which the classifier labeled the examples for this posture. The numbers of the column and the row headers correspond to the posture numbers in Figure 4. The matrix summarizes the results of all 10 runs and the values were normalized to 1 (matrix value / (45 test examples per posture * 10 runs)). Due to rounding bias, some columns do not sum up to one. The matrix shows that the postures “Two” (3), “Ring” (5), and “Grasp” (6) show the best recognition performance. Some examples of the posture “Fist” (2) were assigned to posture “Hand Open” (1). The postures “Hand Open” (1), “Fist” (2), and “Ring” (5) received some false-assignments by “Fist” (2), “Pointing” (4), and “Hand Open” (1), respectively. Only “Two” (3), “Pointing” (4) and “Grasp” (6) received no false-assignments.

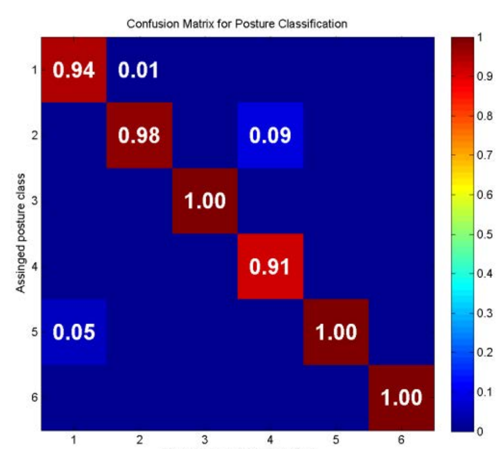


Figure 5: Confusion matrix for experiment 2.

Discussion

The experiment revealed that it is possible to distinguish between finger postures including thumb, index finger, and middle finger with an average of 97% correct classified test examples. Most miss-assignments can be explained by the limited range of the electric field. For example, during the execution of “Hand Open” (1), the thumb was sometimes too far away from the ring and was consequently, classified as “Ring” (5) or “Two” (3). If the fist was not fully closed, posture “Fist” (2) was sometimes classified as “Hand Open” (1). The posture “Pointing” (4) performed worst because it produces a similar signal pattern to the posture “Fist” (2) if the middle finger was in effective field range. Overall, all postures had in average over 90% of correct results and are, thus, suitable for the usage with eRing.

Experiment 3 – Dynamic Finger Gesture Recognition

After we evaluated the feasibility of eRing to recognize finger postures we aim now to show the feasibility to recognize dynamic finger gestures involving thumb, index and middle finger. In this experiment, we tested the recognition of six gestures (Figure 6). The data in this experiment was recorded under the same conditions as experiment 2 for the posture recognition.

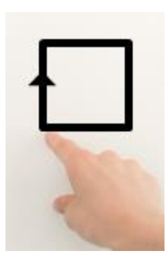
In difference to the posture recognition, we applied the *z*-score normalization to each gesture example before we ran the classification.

Results

The results of experiment 3 are mapped into a confusion matrix (Figure 7) in the same way as described in the results of experiment 2. It shows a multifarious distribution of miss-classified examples. The average classification rate of each class was 0.91. The outliers are “Drop” (6) with 1.00 and “Square” (3) with 0.80. The overall mean error rate of the 10 runs in experiment 3 was 0.094. The gestures “Circle” (2) and “Square” (3) had the broadest distribution

(1) Wipe

(2) Circle Left



(3) Square Right

(4) Pinch

(5) Snap

(6) Drop

Figure 6. Finger gestures used in experiment 3.

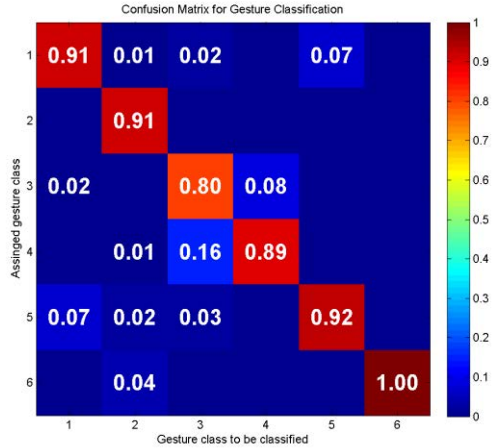


Figure 7: Confusion matrix for experiment 3.

of miss-classified examples. Most miss-classified examples of the gesture “Square” (3) were assigned to “Pinch” (4) and vice versa.

Discussion

This experiment showed that eRing is able to detect a broad range of gestures. It enables the recognition of index finger movements (2, 3, 5, 6) as well as of thumb (1, 4) and middle finger (5) movements close to the index finger. The same issue with the limited field range as observed in experiment 2 occurs in context with the dynamic gestures. If the fingers are further away from the ring than they should, the gesture is miss-classified. For example, if the thumb is out of the field range during the “Wipe” (1) gesture, then it is classified as “Snap” (5) or “Square” (3). However, in spite of the lower overall recognition rate in comparison to the postures, all gestures are suitable for the usage with eRing.

CONCLUSION

In this paper we proposed a novel ubiquitous gesture interaction device called eRing and evaluated its feasibility. It consists of a finger ring equipped with four electrodes spanning an electric field around the finger. Wearing eRing on the index finger, finger postures and gestures involving the thumb, index finger and middle finger can be tracked and recognized. The four sensor electrodes consume only about 10µW. The most power consuming part is the microcontroller, so that the power consumption depends almost exclusively on the used microcontroller. In connection with the used 1NN classifier and the LTW similar measure, we provide a concept for an ultra-low power consuming device that can recognize complex gestures on-device.

Experiments showed that despite severe limitations in the prototype and no optimization in the detection algorithm the prototype is a promising foundation for distinguishing finger postures and gestures. To overcome limitations in the range of the electric fields we plan to build a new prototype using an oscillating voltage and a different measuring mode for the variations in the electric field.

In order to simplify the classification and to omit the separation between posture and dynamic gesture recognition, we plan to study different preprocessing methods and features, which work for both.

REFERENCES

1. Bailly, G., Müller, J., Rohs, M., Wigdor, D., and Kratz, S. ShoeSense: A New Perspective on Gestural Interaction and Wearable Applications. In *Proc. CHI 2012*, 1239-1248.
2. Baxter, L. K. Capacitive Sensors: Design and Applications. *IEEE Press on Electronics Technology* (1997).
3. CapSense Arduino library: http://playground.arduino.cc/Main/CapacitiveSensor
4. Dementyev, D., and Paradiso, J. A. WristFlex: Low-Power Gesture Input with Wrist-Worn Pressure Sensors. In *Proc. UIST 2014*, 161-166.
5. Dipietro, L., Sabatini, A.M., Dario, P. A Survey of Glove-based Systems and Their Applications. *Trans. Sys. Man Cyber Part C* 38, 4, (2008), 461-482.
6. eRing code repository: https://github.com/ma-wi/eRing_LM
7. Fukumoto, M., and Tonomura, Y. "Body coupled FingerRing": wireless wearable keyboard. In *Proc. CHI 1997*, 147-154.
8. Grosse-Puppendahl, T. et al. OpenCapSense: A Rapid Prototyping Toolkit for Pervasive Interaction Using Capacitive Sensing. In *Proc. PerCom 2013*, 152-159.
9. Hrabia, C.-E., Wolf, K., and Wilhelm, M. Whole Hand Modeling Using 8 Wearable Sensors: Biomechanics for Hand Pose Prediction. In *Proc. AH 2013*, 21-28.
10. Jing, L., Cheng, Z., Zhou, Y., Wang, J., and Huang, T. Magic Ring: A Self-Contained Gesture Input Device on Finger. In *Proc. MUM 2013.*
11. Keogh, E., and Kasetty, S. On the Need for Time Series Data Mining Benchmarks: A Survey and Empirical Demonstration. In *Proc. KDD 2002*, 102-111.
12. Ketabdar, H., Moghadam, P., Roshandel, M. Pingu: A New Miniature Wearable Device for Ubiquitous Computing Environments. In *Proc. CISIS 2012*, 502-506.
13. Kim, D., Hilliges, O., Izadi, S., Butler, A.D., Chen, J., Oikonomidis, I., and Olivier, P. Digits: Freehand 3D Interactions Anywhere Using a Wrist-Worn Gloveless Sensor. In *Proc. UIST 2012*, 167-176.
14. Kim, J., He, J., Lyons, K., Starner, T. The Gesture Watch: A Wireless Contact-free Gesture-based Wrist Interface. In *Proc. Wearable Computers* (2007), 15-22.
15. LaViola, J. J. 3D Gestural Interaction: The State of the Field. *ISRN Artificial Intelligence* (2013)
16. Mistry, P., Maes, P., and Chang, L. WUW - Wear Ur World: A Wearable Gestural Interface. In *Proc. CHI EA 2009*, 4111-4116.
17. Nanayakkara, S., Shilkrot, R., Yeo, K.P., and Maes, P. EyeRing: A Finger-Worn Input Device for Seamless Interactions with our Surroundings. In *Proc. AH 2013*, 13-20.
18. Rekimoto, J. GestureWrist and GesturePad: Unobtrusive Wearable Interaction Devices. In *Proc. Wearable Computers* (2001), 21-27.
19. Smith, J.R. Electric Field Imaging. Dissertation, MIT (1999).
20. Spiegel, S., Jain, B.-J., and Albayrak, S. Fast Time Series Classification Under Lucky Time Warping Distance. In *Proc. SAC 2014*, 71-78.
21. Xi, X., Keogh, E.J., Shelton, C.R., Wei, L., and Ratanamahatana, C. A. Fast Time Series Classification Using Numerosity Reduction. In *Proc. ICML 2006*, 1033–1040.