A New Method to Prevent Unintentional Child Poisoning

B.M.S. Bahar Talukder, Emil Jovanov, *Senior Member IEEE,* David C. Schwebel, and W. Douglas Evans

Abstract— **Unintentional child poisoning represents an increasingly important health issue in the United States and worldwide, partially due to increased use of drugs and food supplements. Biometric authentication is complex for pill bottles, but we propose a new method of user identification using touch capacitance during bottle-opening attempts. A smart pill bottle could generate an immediate warning to deter a child from opening the bottle and send an alert to parents/guardians. In this paper, we present principle of operation and implementation of a prototype "safe bottle". We present the results of pilot testing with 5 adults and 3 children using support vector machine (SVM) and neural network (NN). From 232 bottle-opening events, our optimized NN generated no false detections of children as adults and four false detections of adults as children. Preliminary results indicate that smart pill bottles can be used to reliably detect children trying to open pill bottles and reduce risk of child-poisoning events.**

I. Introduction

Unintentional child poisoning is a significant public health problem. Of the roughly 2.4 million exposures reported to US poison control centers annually [1], nearly 50% are children under 6 years of age. Further, since not all exposures are reported to poison control centers, experts assume that these numbers – which total over 1.1 million exposures to children ages 0-5 years annually – are underestimates. Child-resistant caps have saved countless lives over the past half-century, but they are not foolproof. Federal regulations permit child-resistant caps to be used legally if they are opened by 20% of children ages 42-51 months within 10 minutes (16 CFR 1700.20), far from a satisfactory safety margin. Moreover, child-resistant caps are frustrating to many consumers, including elderly and disabled individuals.

There are two primary reasons for increasing child poisoning rates. First, medications are more available than ever in our homes, including prescription drugs, over-the-counter medicines, vitamins, herbs, and dietary supplements, thus increasing the chances a young person may swallow one of these products. Second, due to our fast-paced lifestyles, family members might forget to properly store medicine away from children's reach, or a parent or grandparent might forget a pill bottle is in a handbag or briefcase [2]. A recent Safe Kids report suggests that young children who discover medicine while adults weren't looking caused 95% of unintentional medication overdose ER visits. 5% are due to dosing errors.

New sensing technologies may detect a variety of hazardous events. Biometric authentication has attracted attention from many researchers recently and could ensure that the right person is accessing the right data. Currently, several methods of Biometric authentication are available on the market. The most popular form of biometric authentication is the image processing technique applied on a 2D image (Face, Fingerprint, Iris, Palm-print, etc.) to extract unique physiological features of the user [3]–[6]. Researchers propose techniques using palm features, such as palm-print [7], [8] and palm vein network [9], as well as pattern recognition techniques similar to the finger-print based authentication. Recently, Nascimento et al. [10] showed that palm geometry can be used as a good metric of biometric authentication. Zhang et al. [11] proposed another technique whereby 3D surface curvature maps were used for feature extraction. High accuracy on these proposed methods imply that hand geometry (shape) and surface curvature vary from person to person and influence contact area with an object. This difference in contact area should result in different capacitive value in the sensor. Cua et al. [12] showed that skin friction (coefficient) may vary among people (0.02-0.34), leading people to hold the same object at different pressures and with different styles. Similarly, Barel et al. [13] showed that pressure variation in the skin may cause variations in skin capacitance (up to 43%). Together, these two articles signify that palm capacitance can vary because of individual holding styles.

We propose development of smart bottle technology to detect hazardous events and provide instant alarms and warnings to parents and guardians, wherever they are. Smart pill bottles are increasingly used for monitoring of drug compliance (e.g. AdhereTech smart pill bottle [14]). We plan to expand connectivity of the smart pill bottle with detection of critical events to prevent child poisoning. The same technology can be used to reduce child poisoning from other household products. In this paper we present a new

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B.M.S. Bahar Talukder is with the Electrical and Computer Engineering Department, University of Alabama in Huntsville, Huntsville, AL 35899 (e-mail: bt0034@uah.edu)

Emil Jovanov is with the Electrical and Computer Engineering Department, University of Alabama in Huntsville, Huntsville, AL 35899 (e-mail: emil.jovanov@uah.edu, phone: 256-824-5094; fax: 256-824-6830).

David C. Schwebel is with the Department of Psychology, University of Alabama at Birmingham, Birmingham, AL 35294, USA (e-mail: schwebel@uab.edu).

W. Douglas Evans is with Milken Institute School of Public Health, The George Washington University, 2121 I St NW, Washington, DC 20052 (e-mail: wdevans@gwu.edu)

concept for identification of class of users (child vs. adult), implementation of the prototype safe bottle, and pilot study data used to evaluate feasibility of the use of safe bottle for prevention of unintentional child poisoning.

II. METHODS

Present generations of microcontrollers support direct measurement of capacitance on several pins. Microcontrollers, such as NXP MKL26Z64VFT4 used in Teensy LC platform [15], support capacitive measurements from up to 11 pins with default accuracy of 0.02 pF and measurement time in the order of 1 ms. The microcontroller features low power consumption, small 48QFN package, and low price.

A. *Safe Bottle Implementation*

We implemented the prototype safe bottle with 15 capacitive segments around a standard pill bottle as shown in Fig. 1. Capacitive segments consist of copper tape strips insulated with clear plastic tape. To facilitate high speed sampling we used two microcontroller boards: Teensy 3.2 [16] is used to measure capacitance from 6 channels and Teensy 3.6 microcontroller [17] is used to measure capacitance from 9 channels and save data to an on-board micro SD card. Capacitance was sampled at 50Hz throughout the experiment. Teensy 3.6 serves as the master controller that initiates measurements in each cycle. The prototype is battery powered, with battery and both controllers hidden inside the bottle. All segments are isolated from the user with clear tape.

Figure 1. Prototype safe bottle

B. *Experiment*

The pilot experiment was organized to evaluate feasibility of the use of capacitance to detect two classes of users: *children* (in our pilot experiment, up to 10 years old), and *adults* (over 20 years old). We observed that older children can have larger hands than some adults, and therefore excluded ages 10-20. The experimental protocol was approved by the IRB at the University of Alabama at Birmingham (approval number IRB-300000806). We asked five adults and three children (see Table I) to open and shut the bottle 30 times, simulating taking a pill out of the bottle. Capacitance of all segments were constantly recorded with sampling frequency of 50 Hz. Subjects were not instructed how to hold or open the bottle in order to capture their natural patterns of bottle use. We collected a total of 232 events during the experiment.

C. *Signal Processing*

All signals are processed off line using Matlab 2017b. A typical example of the change of capacitance during bottle opening is shown in Fig. 2. Default capacitance (C_{def}) before touch for the segment in Fig. 2 is 24 pF, and it increases to over 50 pF (relative change of 26 pF) during touching and opening of the bottle.

TABLE I. RELATIVE CHANGE OF THE MOST IMPORTANT DERIVED PARAMETERS MEAN(STDEV); TOTAL RELATIVE CAPACITANCE CHANGE (TRCC), NORMALIZED TRCC (TRCCN), AND MID-SENSE POSITION (MSPOS)

Subject	Age	Sex	tRCC	tRCCN	mspos
A1	26	M	12.98 (3.43)	6.05 (1.11)	4.78 (0.55)
A2	57	M	17.71 (2.02)	7.91 (0.67)	5.64 (0.24)
A3	26	M	26.18 (4.12)	7.11 (2.05)	5.85 (0.37)
A4	24	F	15.01 (2.67)	6.62 (1.46)	5.16 (0.37)
A5	22	M	18.29 (4.29)	6.73 (1.78)	5.39 (0.43)
C1	5	M	5.56 (2.10)	4.94 (0.87)	3.78 (0.49)
C2	10	F	4.00 (0.93)	3.97 (0.77)	3.10 (0.46)
C3	7	F	4.25 (1.40)	4.52 (0.82)	3.53 (0.47)
Adults	31(14.6)		18.13(5.68)	6.90 (1.60)	5.37 (0.55)
Children	7.3(2.5)		4.51(1.62)	4.45 (0.89)	3.46 (0.54)

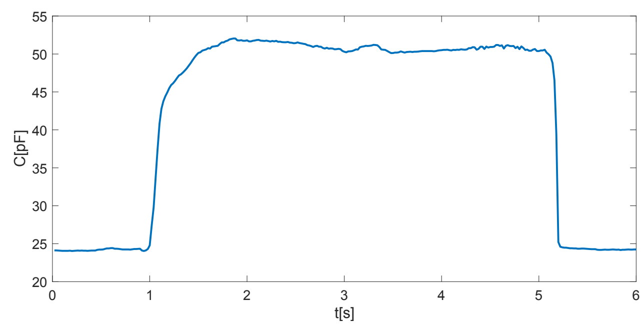

Figure 2. Typical change of capacitance of a segment during opening of the bottle

Each channel is first filtered using a 3 point median filter. The relative change of capacitance CR_i of the segment i (C_i) with default capacitance C_{def} is calculated as

$$CR_i = \frac{C_i - C_{def}}{C_{def}} \quad (1)$$

Total capacitance C_t is calculated as:

$$C_t = \sum_{1}^{15} CR_i \quad (2)$$

The region of interest (ROI) for each touch event is selected as the 500 ms period from the start of touch, detected as a change of C_t that exceeds a predefined threshold. In our preliminary study, we used a threshold that is 20% higher than default total capacitance.

For each touch event, we save the average value of the relative change of capacitance for each segment (15 values) and calculate the following parameters:

- Total relative change of capacitance (*tRCC*) represents the sum of all relative changes CR_i, $i=1..15$

- Maximum change of capacitance: $CR_{max} = \max(CR_i)$, $i=1..15$
- Normalized change of capacitance: $CRN_i = CR_i)/ CR_{max}$, $i=1..15$
- Normalized total relative change of capacitance: *tRCCN*
- Mid segment position *mspos* is calculated as a center of gravity of the sorted set of relative capacitances $\{ CR^{sort}{}_{i}, i=1..15 \}$

$$mspos = \frac{\sum_i CR_i^{sort} * i}{\sum_i CR_i}$$

Touch capacitance depends on skin properties (e.g. wet hands will have significant higher capacitance than dry hands for the same user). Therefore, we use normalized change (*tRCCN)* to get a value that depends on touch area, not skin condition.

An example of the absolute change of capacitance for a child and an adult for each segment is shown in Fig. 3. Note that because of the circular pattern of capacitive segments with no markers on the bottle, each touch event will have different segments with maximum change.

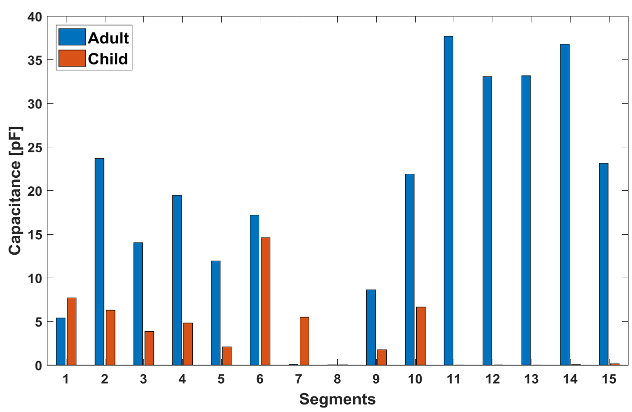

Figure 3. An example of the absolute change of capacitance during opening of the bottle for adult and child

A sorted set of normalized changes of capacitance is represented in Fig. 4. It can be seen that adults consistently have a larger contact area and therefore more segments with significant changes than children. Extracted parameter *mspos* represents a measure of the distribution of segments during touch events.

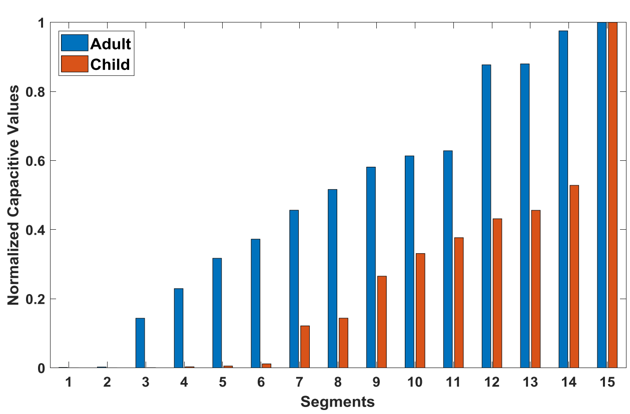

Figure 4. Sorted and normalized capacitance of all segments for adult and child; figure represents the same data set from Fig. 3

For classification of events we used Support Vector Machine (SVM) and Neural Network (NN) as toolboxes in Matlab 2017b.

For SVM training we randomly selected 2/3 of events for each user, and validation is performed using the remaining 1/3 of events (typically 20 and 10 events respectively for each user). For NN, 70% of events were used for training, 15% for validation and 15% for testing.

III. Results

Preliminary results from our pilot study indicate significant changes of parameters between adults and children, as represented in Table I.

The average value of *tRCC* for adults was 18.13±5.68 (mean±standard deviation) and for children was 4.51±1.62; *tRCCN* for adults and children was 6.90±1.60 and 4.45±0.89, respectively. A single parameter classification has limited applicability due to the significant variability of results between experiments and overlap of between groups. Change of tRCC and tRCCN is represented in Fig. 5.

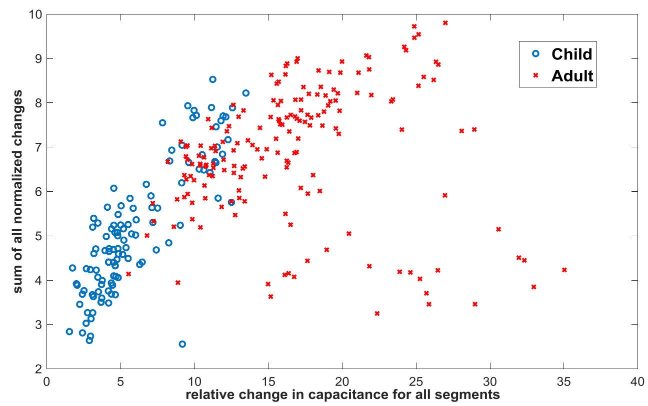

Figure 5. Change of *tRCC* and *tRCCN* for adults and children.

To assess performance of the developed system, we define as a **critical event** when "children attempt to open the bottle" (true positive detection TP when child is detected as a child). Other events include "child detected as adult" (false negative FN), "adult detected as child" (false positive FP), and "adult detected as adult" (true negative TN). We specify detection rates as follows:

- Sensitivity = TP/(TP+FN)
- Accuracy = (TP+TN)/(TP+FP+FN+TN)

The receiver operating characteristic (ROC) curve of the NN classifier with 18 parameters described in Section II.C is presented in Fig. 6.

Our goal is to achieve maximum sensitivity – detection of critical events that can lead to unintentional child poisoning, which in our case is a child detected as an adult. In real-world applications, false detections of an adult as a child would only create false alarms for parents/guardians.

The results of NN classification are presented in Table II. The best performance was achieved by using 3 extracted parameters and no raw data.

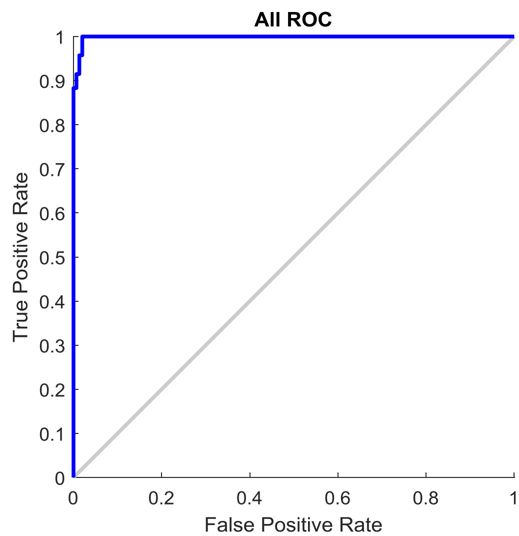

Figure 6. ROC curve of the best NN user classfier.

TABLE II. CLASSIFICATION OF USERS USING NEURAL NETWORK WITH VARIABLE NUMBER OF INPUT PARAMETERS (1/2/3/18)

Parameters	# inputs	FN	FP	Accuracy
tRCC	1	2	5	81.1%
tRCC/tRCCN	2	0	3	91.9%
tRCC/tRCCN/midpos	3	0	1	97.3%
tRCC/tRCCN/midpos/Ci	18	1	2	91.9%

Classification of events using SVM and NN produced similar results. NN implementation provides more flexibility, particularly for future real-time implementation on the bottle.

Results of the SVM classifier are presented in Table III. The SVM classifier uses only three parameters: *tRCC*, *tRCCN*, and *mspos*. Presented results were obtained with 10 runs and random selection of records for training and testing. The critical parameter for our application, false detection of a child as adult, is 2.08% for the SVM classifier with three extracted parameters. We used MATLAB auto optimizer to select the suitable kernel function and to optimize other hyperplane parameters.

TABLE III. CLASSIFICATION OF USERS USING BINARY SVM CLASSIFIER USING *TRCC*, *TRCCN*, AND *MSPOS;* AVERAGE FOR N=10 RUNS; TRAINING SET ADULT/CHILD 102/64; TEST SET ADULT/CHILD 49/30

Adult				Child			
False pos	False neg	Sensiti-vity	False pos [%]	False pos	False neg	Sensit-ivity	False pos [%]
1.0	0.9	98.16%	2.08%	0.9	1.0	96.67%	3.10%

IV. CONCLUSION

In this paper we presented a new approach to prevention of unintentional child poisoning. Our pilot study indicates that the approach is feasible and can be implemented in pill bottles and other everyday objects that could harm children. Smart pill bottle integrated into Internet of Things [18] can generate aural and visual warnings on bottles to deter children, and immediately notify parents/guardians about possibly critical events.

Device intelligence will allow personalization of signal processing algorithms and setup according to user's preferences.

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