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1 **Application of the Teagar-Kaiser energy operator and wavelet**  
2 **transform for detection of finger tapping contact and release times**  
3 **using accelerometer**

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## 19 **Abstract**

20 The Teager-Kaiser energy operator (TKEO), when applied to a signal gives an estimation of the  
21 instantaneous energy of that signal. It, therefore, accentuates both frequency and amplitude  
22 changes in a signal. To date, it has been primarily used in communications systems and most  
23 popularly in electromyographic signal analysis to detect bursts of muscle activity, however, it  
24 has the potential to be used in a number of applications including accelerometer and movement  
25 data.

26 A new algorithm was developed which used the TKEO to detect contact times during a finger  
27 tapping task from accelerometer data recorded from the index finger. The accuracy of the  
28 algorithm was assessed in 7 healthy control subjects during continuous finger tapping across a  
29 range of frequencies from 0.5Hz to 2.5Hz. The algorithm proved to be sensitive, correctly  
30 identifying at least 99% of all contacts in each of the finger tapping conditions that were tested.  
31 The mean absolute error of the contact detection is  $14.7 \pm 6$  ms, while the mean absolute error  
32 of the release detection is  $36.5 \pm 36.3$  ms. The proposed algorithm provides a method for the  
33 automatic detection of the temporal occurrences of the events of the finger tapping task using  
34 only a tri-axial accelerometer. The approach presented provides a means for objective  
35 assessment of finger tapping tasks for evaluation of the fine dexterity of the upper limb

## 36 **Introduction**

37 Finger tapping is one of the tasks used in assessing motor function in a number of movement  
38 disorders including Parkinsons Disease and Huntingtons Disease [1]. At present, this task is  
39 assessed subjectively by a clinician to determine how the current disease state is affecting the  
40 fine motor skills of the respective patient. Due to the subjective nature of the movement  
41 disorders rating examinations, there is a potential for inter-rater variability in outcome ratings of  
42 the exam [2]. Hence, there is a current need for a low cost, objective measure to assess the  
43 function of the participants during the various tasks of the movement disorders rating scale  
44 examinations.

45 Tri-axial accelerometers provide a low-cost, lightweight and portable solution to accurately  
46 measure the complex movements of a body. They are increasingly popular in studies of human  
47 movement analysis to study gait and other clinical tasks [3], [4].

48 A number of different sensor types have been used to assess the finger tapping task such as  
49 gyroscopes, hall-effects magnetic sensors, touch sensors and accelerometers [5]–[7]. These  
50 studies use characteristics of the recorded signals to infer features of the finger tapping task such  
51 as the temporal occurrences of contact and release of the index finger and the thumb as well as

52 quality of the movement during the task. None of these studies, however, validated the detection  
53 of these features using robust ground truth data.

54 The Teager-Kaiser energy operator estimates the energy of a signal which is derived from the  
55 instantaneous amplitude and instantaneous frequency of the signal. Thus, it can be used to  
56 detect instantaneous changes in either amplitude or frequency in a given signal. Due to its  
57 abilities to enhance high amplitude and frequency changes in signals, the TKEO has been used  
58 to detect the onset of muscle activity in the electromyogram signal during various movement  
59 tasks [8], [9], to image contrast enhancement [10]. In this paper, we introduce a novel algorithm  
60 that uses the TKEO in conjunction with a variant of the discrete wavelet transform, the Maximal  
61 Overlap Discrete Wavelet Transform (MODWT), to find the temporal occurrences of the index  
62 finger and thumb contacts and releases during finger tapping. The performance of the proposed  
63 algorithm is assessed in healthy control subjects where contact times are recorded using touch  
64 sensors located on the contact surfaces of the index finger and thumb respectively.

## 65 **Methods and Materials**

### 66 *A. Participants*

67 7 healthy, young participants (2 female, age:  $24.57 \pm 1.51$ ) gave their informed consent to  
68 participate in the study. Research ethics approval was obtained from the board of Research  
69 Ethics, University College Dublin before the commencement of the study.

### 70 *B. Experimental Protocol*

71 An aluminium splint was placed over the subjects index finger to restrict movement at the inter-  
72 phalangeal joints. and secured with tape. A 3-axis digital accelerometer (Grove ADXL345,  
73 200Hz) was then secured to the lateral aspect of the splint using tape. Subjects were instructed  
74 to tap the distal phalanx of the index finger (or as close as possible) with their thumb while  
75 keeping their forearm and hand in the prone position (Fig. 1). For the purposes of validation of  
76 the algorithm, touch sensors were applied to the contact surfaces of the index finger and thumb  
77 to provide a ground truth measure that accurately determined the occurrences of contact  
78 between the index finger and thumb. The output of the contact sensors was then compared to the  
79 output of the proposed TKEO algorithm to assess the accuracy of the algorithm.

80 Subjects were instructed to tap their index finger to their thumb in time with a metronome for a  
81 30 second period. The metronome was set to five different frequencies (0.5, 0.625, 0.833, 1.25,  
82 2.5 Hz). A final sixth trial consisted of un-queued tapping where subjects were instructed to tap  
83 as fast as possible without a metronome beat to follow.

### 84 *C. Contact Time Detection Algorithm*

85 To calculate the temporal occurrences of the contact and release events of the index finger and  
86 thumb during the finger tapping task, a combination of high-pass filtering using the MODWT  
87 and MRA as well as the detection of simultaneous changes in frequency and amplitude of the  
88 signal using the TKEO algorithm were implemented in a novel algorithm.

89 1) The raw accelerometer signal from the major axis of motion was filtered using a  
90 maximal overlap discrete wavelet transformation with a Haar mother wavelet. The Haar  
91 wavelet was chosen for its ability to accentuate high frequency and amplitude changes  
92 in a signal.

93 2) Following the wavelet transform, a multi-resolution analysis was performed to ensure  
94 zero-phase filtering of the processed signal as it is imperative to retain temporal  
95 resolution for this application. The MODWT acts as a series of zero-phase filters over  
96 the signal [11]. One very useful property of the MODWT is that it can be used to form a

97 multi-resolution analysis (MRA). A multi-resolution analysis allows for the  
 98 reconstruction of the original time series signal into a sum of several new series, each of  
 99 which is related to variations in the original signal at a given scale.

100 3) The first level (highest-frequency level) of the multiresolution analysis was then  
 101 processed using the TKEO to further accentuate the high-frequency changes in the  
 102 signal which corresponded to the contacts of the index finger and the thumb. The  
 103 following formula [12] is used to compute a symmetric discrete time estimation of the  
 104 TKEO where  $T_s$  is the sampling period and  $n$  is the sample number:

$$\Psi_n = \frac{2x_n^2 + (x_{n+1} - x_{n-1})^2 - x_n(x_{n+2} + x_{n-2})}{4T_s} \quad (1)$$

105

106 4) To smoothen the signal before using a peak-finding algorithm to determine the  
 107 contact-times, a moving maximum window followed by a moving mean window were  
 108 used.

109 5) A peak-detection algorithm was then employed to find peaks in the smoothened and  
 110 processed signal which correspond to the contact events between the index finger and  
 111 the thumb.

112 6) Once the contacts were identified, a further peak finding algorithm was used to  
 113 search between the peaks marking the contacts between the index finger and thumb to  
 114 find the point of release of the index finger and the thumb.

#### 115 ***D. Data Analysis***

116 The data recorded from the participants were analysed using MATLAB (The Mathworks Inc.,  
 117 Natick, MA, USA). Since the major axis of motion during the task was along the Y-axis of the  
 118 accelerometer (Fig. 1), the data from this axis was used to detect the events of the finger tapping  
 119 task.

#### 120 ***E. Validation***

121 The contact times detected by the touch sensor were then compared to the times compared to the  
 122 algorithm by calculating the mean error, sensitivity, specificity and accuracy. The mean  
 123 absolute error can be calculated as follows:

$$MAE_{taps} = \sum_{k=1}^{k=N} | actual_k - detected_k | \quad (2)$$

124

125 where N is the total number of contacts between the index finger and thumb in the given  
 126 recording, actual indicates the contact as determined by the touch sensor and detected indicates  
 127 the contact as determined by the algorithm.

$$Sensitivity = \frac{TP}{(TP + FN)}\%. \quad (3)$$

128

129 Sensitivity was calculated as in (3). True positives (TP) were contacts that were identified by  
 130 both the detection algorithm and by the touch sensors. False negatives (FN) were contacts that  
 131 were not detected by the algorithm but were detected by the touch sensors.

## 132 Results

133 The mean absolute error and its standard deviation for both the contact and release times as well  
 134 as the sensitivity of the detection algorithm are displayed in the following table.

135 TABLE I MEAN ABSOLUTE ERROR AND SENSITIVITY VALUES FOR THE CONTACT  
 136 AND RELEASE TIMES AS DETECTED BY THE TKEO ALGORITHM RELATIVE TO  
 137 THE TOUCH SENSOR DATA.

Frequency of Metronome (Hz)	Mean Absolute Error of Contact Times (ms)	Mean Absolute Error of Release Times (ms)	Sensitivity (%)
0.5	15.0 (9.6)	43.9 (61.7)	100
0.625	14.9 (7.5)	28.2 (36.5)	100
0.833	16.4 (7.6)	32.5 (40.7)	99.43
1.25	15.3 (6.5)	33.5 (46.2)	99.25
2.5	14.9 (6.6)	25.3 (35.4)	99.06
N/A	14.2 (4.8)	43.4 (31.3)	99.02

138

139 The results show that the algorithm is extremely sensitive to the finger tapping action as the  
 140 sensitivity of the algorithm is greater than 99% for all conditions, with the lower tapping  
 141 frequency conditions being the most sensitive. The mean absolute error of the algorithm is  
 142 similar for all conditions which would suggest an inherent offset in the algorithms detection of  
 143 the contacts.

144 For the release times however, the accuracy of the algorithm was lower. This is most likely a  
 145 result of using the first level multi-resolution analysis signal. The first level MRA signal acts as  
 146 a high-pass filter to the raw EMG signal, passing only the high frequency components. Since the

147 opening action of the index finger and thumb is a relatively low frequency action, it may be  
148 more desirable to use a higher level of the MRA analysis to detect these more accurately.  
149 Depending on the frequency of the tapping action however, the particular MRA level that will  
150 detect the release action will change in an unpredictable manner making the accurate detection  
151 of the release events rather difficult.

152 Fig. 3 displays histograms that show the time shift of the detected contacts relative to the actual  
153 contacts as determined by the touch sensors. It is clear to see that for all conditions, most of the  
154 contacts were identified within 50ms of their actual occurrence.

155

156

## 157 **Discussion**

158 The finger tapping task is a common component of examinations of motor function in various  
159 motor disorders [2], [13]. It provides an estimation of the patients' capabilities of fine dexterity  
160 movements, which are often some of the first symptoms to appear in movement disorders such  
161 as Parkinson's Disease [14].

162 Instrumentation of the finger tapping task using inexpensive tri-axial accelerometers will  
163 increase the potential for the finger tapping assessment as it will allow for an in-depth analysis  
164 that is not possible using only a visual assessment. It will also provide objective results that will  
165 remove interrater variability that is inherently introduced by the current subjective visual  
166 examinations [2], [15].

167 During the finger tapping task, the contact instance of the index finger with the thumb is  
168 represented by a simultaneous increase in the instantaneous amplitude and frequency of the  
169 acceleration signal recorded from the tip of the index finger. Using this knowledge, it is possible  
170 to make use of the Teager-Kaiser energy operator along with the maximal overlap discrete  
171 wavelet transform as a form of high-pass filter to accurately detect the temporal occurrences of  
172 the contact events. Although the TKEO has previously been used in a number of applications  
173 [8]–[10], its use in conjunction with the MODWT for the detection of finger tapping events  
174 from an accelerometer signal has not been previously explored.

175 A novel algorithm was developed that uses MODWT in conjunction with the TKEO to detect  
176 the temporal events of the finger tapping task. The algorithm was validated using ground truth  
177 data recorded from touch sensors placed on the contact surfaces of the index finger and the  
178 thumb. The performance of the algorithm was evaluated using the mean absolute difference, its  
179 standard deviation and the sensitivity measure for both the contact and release times. The results  
180 of the evaluation show that the algorithm was able to positively identify at least 99% of the  
181 contacts between the index finger and the thumb under each of the finger tapping conditions that  
182 were tested.

183 The mean absolute difference of the contact times were  $14.7 \pm 6$  ms over all of the finger  
184 tapping conditions examined. The mean absolute difference for the release times however, were  
185 less accurate ( $36.5 \pm 36.3$  ms) for a number of reasons. The filtering process using the MODWT  
186 decomposes the signal into a number of "levels", each level effectively acting as a band-pass  
187 filter with decreasing centre frequencies on the signal. The first level therefore contains the  
188 highest frequencies in the signal. As the release action of the finger tapping task is a relatively  
189 low frequency event compared to the contact action, it may be represented more accurately by a

190 higher level decomposition of the MODWT. Due to the changing frequency of tapping in the  
191 various conditions that were tested, it is difficult to choose an appropriate level that consistently  
192 contains the release events.

193 Further analysis involving both older healthy and older populations affected by movement  
194 disorders will be required to validate the use of this algorithm during episodes of tremor, chorea  
195 or other unintentional movements. The results of the validation of this algorithm suggest that it  
196 is possible to identify the temporal events of the finger tapping task in an inexpensive, objective  
197 and accurate manner using only a tri-axial accelerometer.

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201 **References**

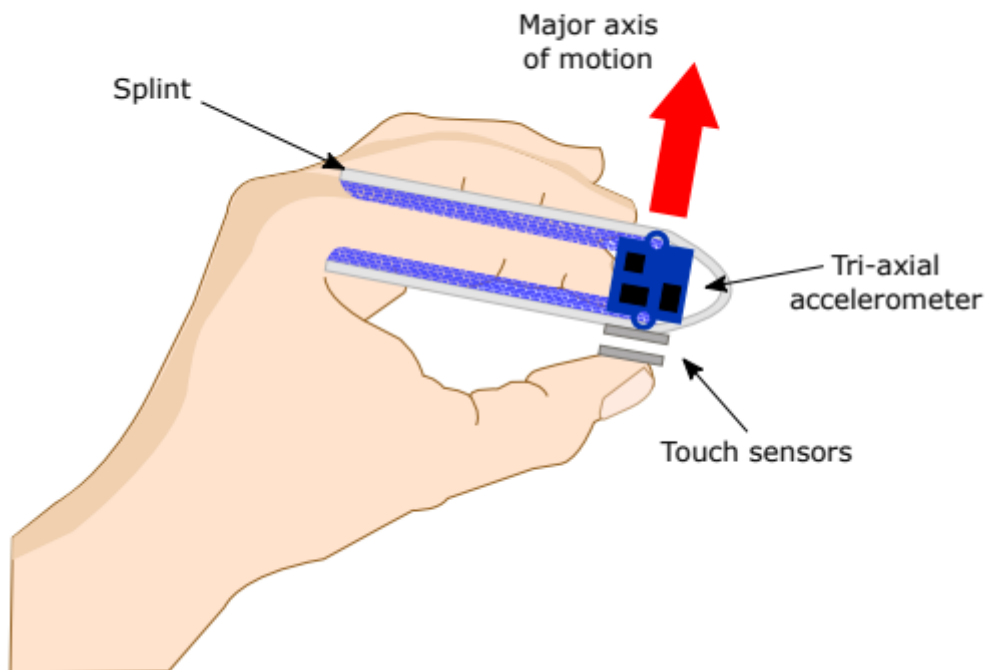
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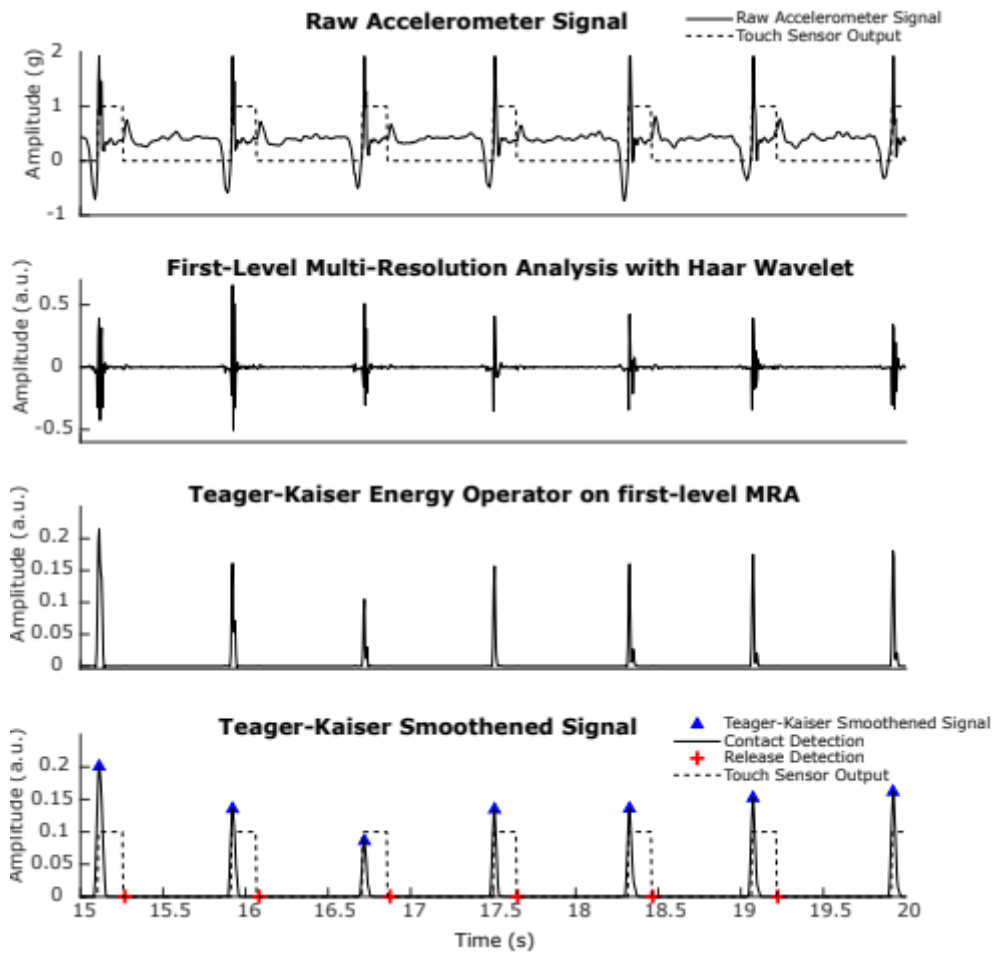
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## 252 Figures



253

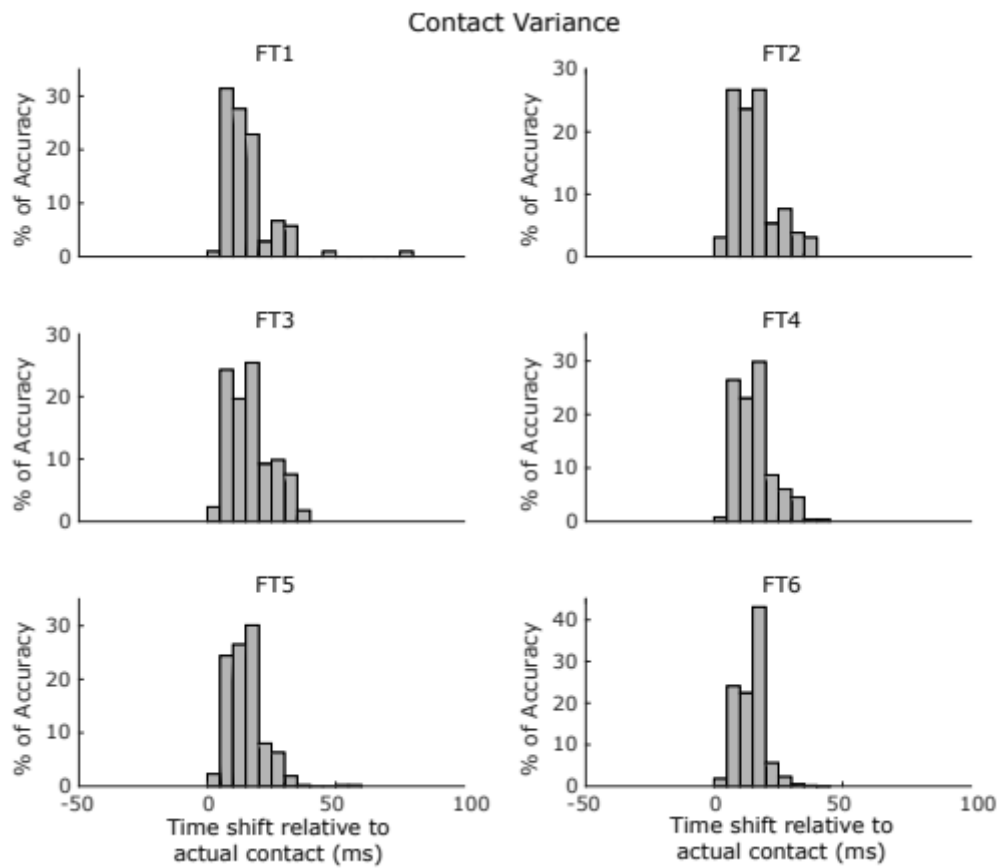
254 **Fig 1:** Illustration of the experimental set-up. A splint is attached to the subject's index finger.  
 255 An accelerometer is then attached to the lateral aspect of the splint. Touch sensors were placed  
 256 on the contact surfaces of the index finger and thumb to provide ground truth data for the  
 257 contact times.



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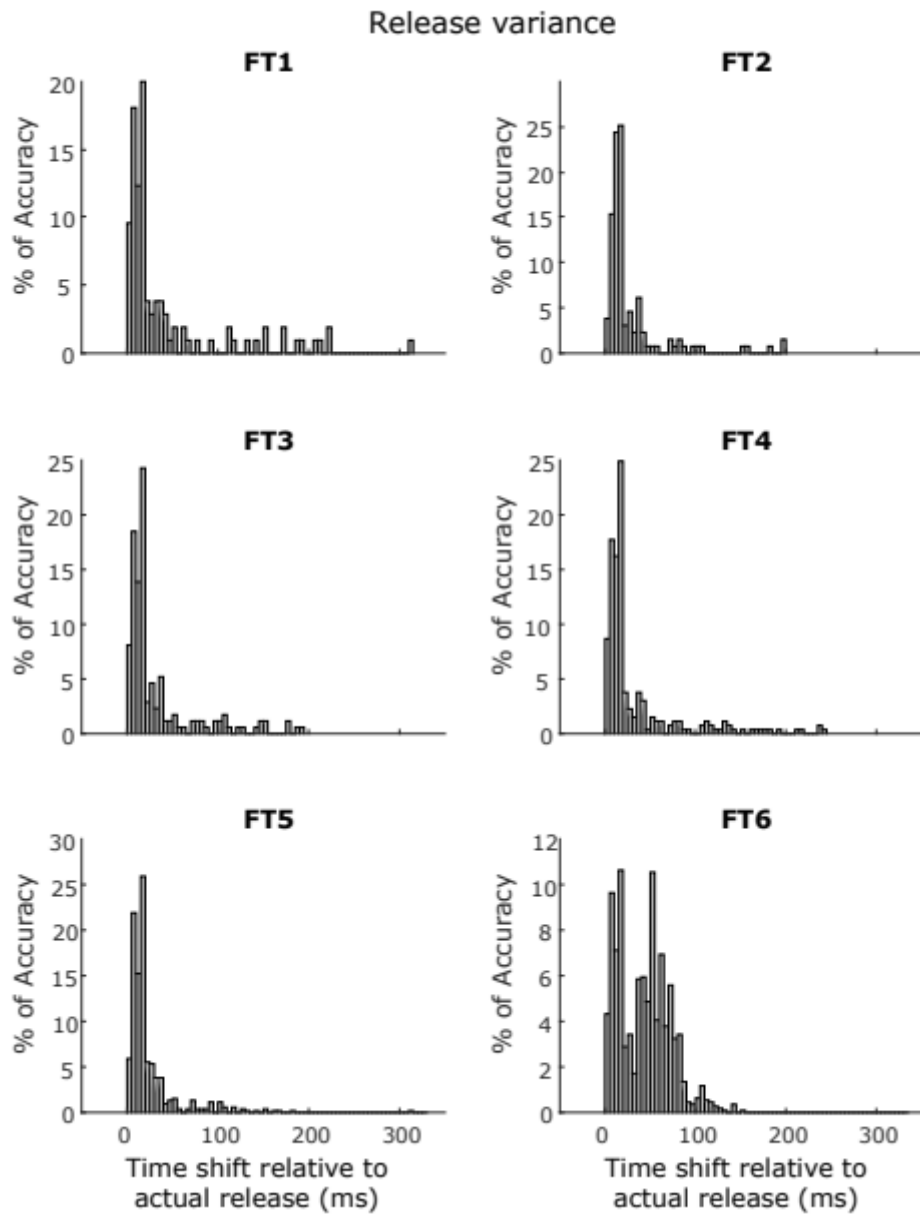
259 **Fig 2:** Processing steps of the raw accelerometer signal to the final TeagerKaiser Energy signal  
 260 that is used to determine the contact instances during the finger tapping task.

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262

263 **Fig 3:** Histograms showing the distribution of the difference in detected contact times vs the  
 264 actual contact times as determined by the touch sensors.



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266

267

**Fig 4:** Histograms showing the distribution of the difference in detected release times vs the actual release times as determined by the touch sensor s.

