When to Type, Talk, or Swype: Characterizing Energy Consumption of Mobile Input Modalities

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***Abstract*—Mobile device users use applications that require text input. Today there are three primary text input modalities, soft keyboard (*SK*), speech to text (*STT*) and *Swype*. Each of these input modalities have different energy demands, and as a result, their use will have a significant impact on the battery life of the mobile device. Using high-precision power measurement hardware and systematically taking into account the user context, we characterize and compare the energy consumption of these three text input modalities. We show that the length of interaction determines the most energy efficient modality. If the interactions is short, on average less than 30 characters, using the device *SK* is the most energy efficient. For longer interactions, the use of a *STT* applications is more energy efficient. *Swype* is more energy efficient than *STT* for very short interactions, less than 5 characters on average, but is never as efficient as SK. This is primarily due to *STT* enabling the users to complete tasks more quickly than when using *SK* or *Swype*. We also show that these results are independent of "user style", the experience of using different input modalities and device characteristics. Finally we show that *STT* energy efficiency is dependent on application logic of whether speech samples are for a given period of time before transmitting to a server for analysis as opposed to streaming the speech to a sever for analysis. Based on these observations we recommend that the users should use *SK* for short interactions of less than 30 characters, and *STT* for longer interactions. In addition, they should use *STT* applications which uses storing and transmit logic, if they are willing to trade off battery life to *QoE*. Finally we proposed the development of an adaptive storing and analyze *STT* to improve the energy efficiency of it.**

I. INTRODUCTION

Smart mobile device usage is becoming pervasive. It has been shown in a study of more than 9 million comments in Google play store, that more than 18% of all commented applications have negative comments with respect to their energy consumption [1]. These applications are primarily being used to access content/information, and a recent survey [2] has shown that the top activities of smart mobile device users are accessing the internet, checking mail, chatting and social networking. Additionally, Instant Messaging (IM) is becoming an increasingly popular substitute for Short Message Service (SMS), offering a flexible range of features at no extra cost [3]. Other recent surveys show that users transmit, on average 110 text messages per day [4] and the number of traditional SMS texts being sent is being overtaken by instant messages on chat apps such as *WhatsApp* and *QQ*[1] [7]. Moreover, average message sizes for SMS are reported to be around 56 characters [8] and for *WhatsApp* 80% of the messages are below 40 characters [3].

Given the popularity (volume) and the size of these instant messages and the other activities such as social networking applications that require text input, it is clear that text input is one of the major modes of interaction. Initially, text input was enabled on smart mobile devices via a soft keyboard (*SK*), i.e. typing on the touch screen keyboard. However with *SK*, the users in most cases, need to use both hands to type fast, which is difficult to do whilst "on the move". To address this, speech-to-text (*STT*) [9], [10] and *Swype*, which allows single-hand text input have appeared in the market. With *STT*, speech is captured on the mobile device and sent to a server for processing. With *Swype*, users simply swipe their finger from one letter toward the next of the intended word, and the mobile app attempts to predict the word. *Swype* is gaining popularity not only because it allows single-handed input, but also as it enables faster input compared to *SK* and is more discrete compared to *STT*.

Different users embrace different input modalities based on their habits and familiarity (convenience). The different text input modalities use different hardware components and carry out different amount of processing on the smart mobile device. Therefore these different input modalities consume different amount of energy for completing the same task. For example, *SK* predominantly uses the touch screen, while *STT* uses the microphone for recording and the communication interface for transmitting the speech sampled to a server and receiving the converted text from the server. Users are mostly unaware of the impact of these processing and communications requirements on the energy consumption of their device. Given the large volume of text based interactions users have, knowing the energy implications of the different input modalities will enable the users to make informed decision about which input modality use to minimize their devices' energy consumption, especially when their device is low on power.

There has been significant work done in terms of optimizing

[1]reported to have over 400 and 800 million users respectively[5], [6]

the energy consumption of smart phones when it is being used for purposes such as video streaming [11], web-browsing [12], downloading content [13] and instant messaging [3]. It is also shown that using the least energy efficient application could potentially shorten the battery lifetime by a factor of 2.5 as reported in [3]. However, all these studies have focused on the use/running of the applications, and not on the user interactions. To the best of our knowledge, there has been no prior work in characterizing the energy consumption of user interaction with smart mobile devices. This paper addresses this through a comprehensive empirical study of energy consumption of the three widely used text input modalities, namely *SK*, *STT* and *Swype*. Using high-precision hardware, which measures energy consumption as the true current drain from the device battery and systematically taking into account the user context, we characterize the energy consumption of the three text input modalities.

This paper makes the following contributions:

- The power consumption of all three text input modalities is independent of message length. However, due to the task completion time, for interactions with less than 30 characters, use a soft keyboard is the most energy efficient. For longer interactions speech to text becomes the most efficient.
- The "user style" and experience of using a given input modality has no tangible impact on the power consumption. In addition, the above findings are independent of the device manufacturer and size.
- We find *SK* has the lowest error rate ($<5\%$) among the three input devices, and *STT* has a comparatively higher error rate but differs a lot from different engines. *Swype* (7.6%) is slightly more accurate than *Google STT* (8.3%) on average.
- We also show that for *STT*, the application logic of whether speech samples are for a given period of time before transmitting to a server for analysis as opposed to streaming the speech for conversion, and the usage of extra hardware, e.g. *GPS*, could have an increased power consumption of up to 45%.

Given the average message lengths, our findings can be used to provide some guidance as to the most power efficient input modality use, thus enabling users to trade off convenience against energy usage.

The rest of the paper is organized as follows. *Section* II summarizes the related work. The detailed experimental setup and measurement methodology are presented in *Section* III. We then give the experiment results in *Section* IV and discuss the results that we observe in *Section* V. Finally, *Section* VI concludes the paper.

II. Related Work

Smart mobile device technology is improving rapidly with significant improvements in processing, storage and screen technology. These improvements are placing more and more demands on energy. However, battery technology is not keeping pace with these improvements and is unlikely to do so in the foreseeable future [14]. As a result, the research community has been investigating ways of minimizing the energy consumption of hardware that are more energy efficient exemplified by [15], [16], [17]. Similarly there has been considerable work done to make the applications more energy efficient, by reducing their interaction with hardware and communications. However, there has been limited work that have investigated the user interaction and the impact on energy.

Page [18] investigated the implications typing using a soft keyboard, ITU-T numeric keypad, *Swype* and *Swiftkey* on six different smart phones. He concluded that, *Swype* and *Swiftkey* are the most effective and that they offer substantial benefits to users as typing speeds comparable to when using common computer keyboard could be achieved. However, the study does not investigate the energy consumption different input modalities have. The focus of our work was to examine the energy consumption of the different input modalities and provide a guide to the users as to which modality should used to conserve energy.

Numerous groups have investigated on energy consumption of mobile devices by examining the energy consumption of different hardware components of mobile devices and applications. Carroll and Heiser [19] presented the detailed breakdown power consumption of mobile phone's main hardware components and developed a power model for smart phone. They investigated the energy usage and battery lifetime under different usage patterns by analyzing the power consumption of the various components of a smart phone. They showed the most power hungry components in the phone and identified the most promising areas to focus on improve energy efficiency. Yoon et al. [20] also used kernel activity monitoring as a way of deterring the energy consumption of mobile applications. Using this technique, they were able to estimate the energy usage for online activities. These studies again focused on application behavior as opposed to user interaction.

Perrucci et al. [21] investigated the impact on energy consumption of a smart phone, when using different services such as data, cellular link services and mobile TV. They show that for SMS, the energy consumption was dependent on the cellular network that is used. The overall finding was that GSM consumes less energy when compared to 3G (UMTS). While this finding influences our finding about the *STT* energy consumption, it does not directly address the impact of the input modalities on power consumption. Vergara et al. [3] studied the energy consumption of different instant messaging (IM) applications. They showed that short messages consume as much energy as longer messages and that it is possible to trade off latency for increased energy efficiency. [22] showed that typing notifications results in almost a 100% increase energy consumption. There are also a number of groups focusing on energy consumption of a specific activities such as video streaming, web-browsing and downloading. Trestian et al. analyzed the power consumption for video streaming using different wireless networks [11]. Their result showed the network load and signal quality together have a significant impact on energy consumption. Thiagarajan et al. [12] measured the detailed energy consumption for web browsing using a similar measurement methodology to what is presented in this paper. They optimized the energy needed for web page downloading, rendering, and showed a modified Wikipedia mobile site which can reduce 30% of the energy cost. Energy consumed when downloading via different wireless networks (Wifi, 3G and Bluetooth) was also investigated by Kalic et al. [13]. They proposed an energy consumption model for each communication technology and showed that this model can be used on collaborative downloading to lower the overall energy consumption. All these works, whilst relevant does not address the impact of the input modalities on power consumption.

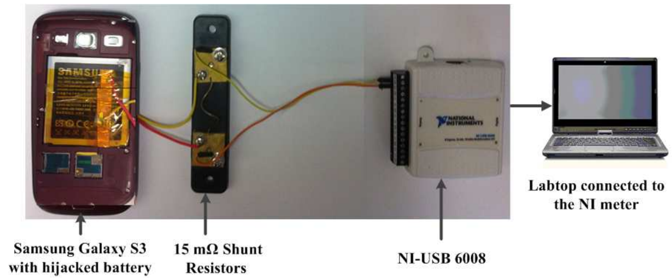


Fig. 1. Power measurement setup

III. Measurement Methodology

Determining the impact of different input modalities on power consumption is difficult because of the large number of dependencies, especially the differences in user interaction styles and the context of use. To address differences in user interaction styles and the impact of context, two sets of experiments, referred to as primary and secondary experiments, were conducted. The primary experiments were aimed at identifying the key differences in power and energy consumption of the three input modalities, and the secondary experiments were aimed at identifying the dependency of the input modality power consumption on user contexts.

Although there exists several software power profilers for Android such as BatteryManager [23] and CurrentWidget [24], that could be used for power measurements, they only enable the measurement of power at fixed, system dependent intervals. For example, Batterymanager only gives the voltage readings whenever there is a percentage change in the battery level. Thus to measure power consumption at a finer granularity, for both sets of experiments, we used a set-up shown in Fig. 1, which has also been used by others [12], [25], [26]. With this set-up, the smart mobile device battery is "hijacked" at one of its terminals, and connected in series with a $15\,m\Omega$ shunt resistor. Then a National Instrument (NI) NI-USB 6008 is used to sample the voltage drop, V, across the shunt resistor at 1 KHz and log the data on to a laptop computer. In addition, for each interaction, the start and end time can be read directly from the voltage log file recorded. Finally we used the standard equation of power, $P = V_b \times I_r$ to calculate the consumed power for each data point, where V_b is the battery voltage and I_r is the current through the shunt resistor. Then the average power consumption for a specific message input modality was computed as the mean value of all the calculated instantaneous power values during the interaction period, as determined by the logged start and the stop times. The total energy consumed for a given input modality was calculated by multiplying average power by the interaction period.

A. Primary Experiments

These experiments were aimed at determining the power consumption of the input modality. Therefore, the experiments used a single fully charged ($\geq 95\%$) Samsung Galaxy S3 smart phone, connected to a 3G or Wifi network. Ten different users were asked to interact with the smart phone by entering the 7 text messages shown in TABLE I, using each of the three input modalities. The message lengths of the messages shown in TABLE I was chosen to be representative of the typical message lengths of text based interactions of smart mobile device based on the message length distributions in [3].

To ensure that the power consumption was only due to the user inputs, all processes on the smart phone were terminated via Android developer options, except for the application used for the experiment. The screen brightness is also set to a fixed level to eliminate any change during the experiment. Furthermore, after each interaction period, the battery level of the smart phone was checked and where necessary the smart phone was recharged, to ensure that the battery level remained at or above 95%.

For *SK*, users entered messages using the Android's default Messager App editor and default Samsung soft keyboard. In order to investigate the impact of user typing style to *SK* power consumption, we developed an Android application that logged the touch down/up time, holding time, pressure and the size of the touch.[2]

For *STT*, the Galaxy S3's built-in *Google STT* application and the STT application available with the *Swype* application, namely *Dragon dictation* were used. They represented the only two *STT* applications available [3]. With Google's *STT* application, each phrase of speech is recorded and then streamed to a Google sever for conversion from speech to text. Once the converted text from the server is received, it is displayed on the screen. Dragon dictation operates in a similar manner, except that it records the speech for given period of time and sends it to a cloud based server for the speech to text conversion. The difference is that Dragon dictation application always tries to record for as long as possible, up to 100 seconds of recording, before sending the whole recorded segment to the server. Because the streaming nature of *Google's STT* application, the communication modules on the mobile device keeps in the active state [27], it consumes more power than *Dragon Dictation*, but has less latency which is reported to result in better user *QoE* as the user can actually see what is being typed

[2]pressure could not be recorded for Samsung S3 because it uses a capacitive screen.

[3]all other applications use the *Google STT* engine.

TABLE I
SEVEN MESSAGES WITH DIFFERENT LENGTHS

Message Length	Message Content
7	A phone
15	That was a test
27	These are few mobile phones
52	This is a test to investigate the energy consumption
79	This is a test to investigate the energy consumption of different mobile phones
102	This is a test to investigate the energy consumption of different mobile phones in different situation
202	This is a test to investigate the energy consumption of different mobile phones in different situation via variety of Android applications and games in various locations in university of New South Wales

in real time. In addition, we also find that, *Google STT* utilizes location service by default, in contrast, *Dragon dictation* does not. This also leads to extra power consumption. As it is the default configuration, we decide to keep the location service on for the primary experiments.

Swype keyboard application was used for the *Swype* experiments. This involved the users simply tracing the characters of a word with their fingers, and the software predicting the word and displaying it on the screen. All volunteers were allowed time to become familiar, if they had not used *Swype* before to minimize the user biases.

B. Secondary Experiments

The objective of these experiments were to investigate the impact of user context on the power consumption of the three input modalities. Thus the experiments involved a single user interacting with three devices, two smart phones (Samsung Galaxy S3, S4) and a tablet (Google Nexus 7) using the same messages used in the primary experiments.

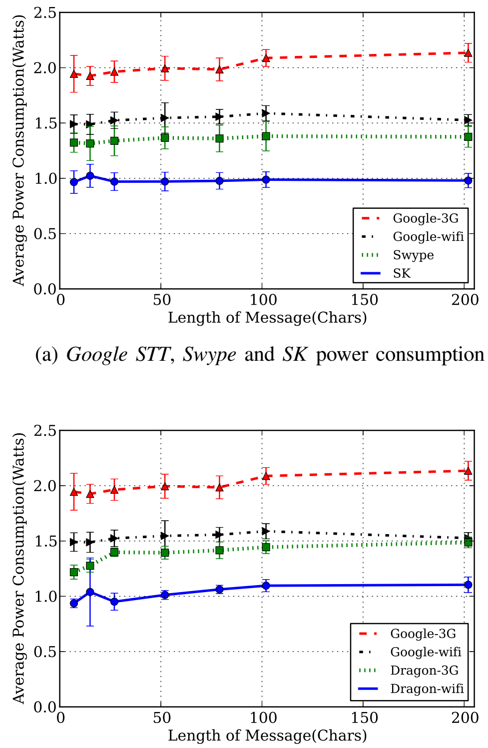
The contexts of the device operating at two different battery charge levels of 95%, 30% and connecting to two different networks (3G/Wifi) in the case of a smart phone were evaluated.

During these experiments to minimize the network connectivity variations, the experiments were repeated in three different locations, namely inside a research lab in the city center, inside a residential apartment in a suburb, and inside a student laboratory. All experiments are repeated three times and the average was used for analysis.

IV. RESULTS

A. Primary Experiment Results

Fig. 2 depicts the average power consumption of different input modalities as a function of message length. As can be seen from Fig. 2(a), the power consumption is independent of message length for all three input modalities. Also as expected, it shows that different input modalities have different power consumption with *Google STT* having the highest power consumption with an average of approximately 2 W when connected to a 3G network, *Swype* the second highest with an average consumption of approximately 1.3 W, and *SK* is the lowest power consumption with an average of approximately 1 W.



(a) *Google STT*, *Swype* and *SK* power consumption

(b) *Dragon dictation* vs *Google STT*

Fig. 2. Power consumption comparison of input modalities

When *Google STT* is used with Wifi network connection, the power consumption is reduced to around 1.5 W. This verifies the findings in [28]. These differences are due to the use of different hardware components which have different power requirements as described in [19], [11]. This is highlighted by the differences in power consumption of the *Google STT* and *Dragon STT* applications. As can be seen in Fig. 2b, the power consumption of the *Dragon STT* application, when using cellular and Wifi networks is approximately 1.03 W and 1.38 W respectively. Its power consumption is around 45% less than *Google STT* application (streaming) in both cases. In addition to the use of the communication module, the *Google STT* uses *GPS* where further increase the energy gap. This will be discussed further in the secondary experiments, *subsection* IV-B .

The time taken to complete a task also varies, depending on the input modality used. Fig. 4a shows the time taken to complete the 7 messages in these experiments, assuming there are no errors. Overall, *STT* takes the shortest time to complete all tasks. As can be seen despite the variation in user "speaking styles", this holds true for all users.

For *SK*, the energy consumption could be influenced by the user "typing style". To investigate this we analyzed effect of touch size and touch duration each key press by developing a simple application which measured the touch time and

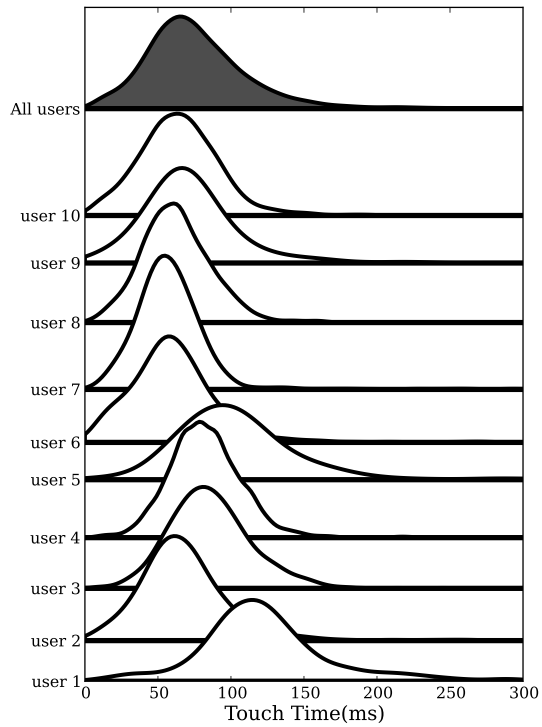
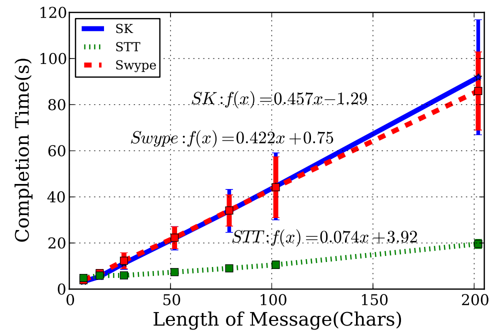
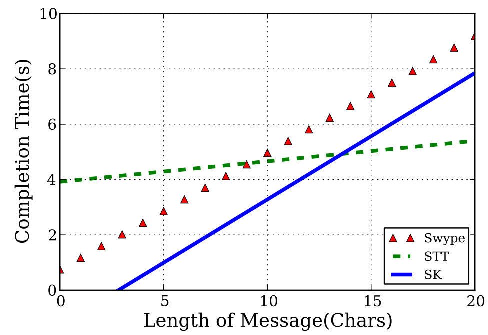


Fig. 3. Probability density function of the touch time for users



(a) Completion time



(b) Zoom in

Fig. 4. Message completion time comparison of three input modalities

duration.

Fig. 3 shows the touch time of users during the experiments, which is done by using Gaussian kernel density estimation. It shows that the difference between the mean touch times of users is approximately $55\,ms$, and 80% of all touches has a touch duration under $90\,ms$.

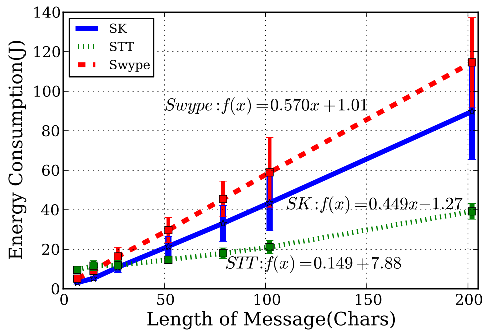
Touch sizes were found to be similar among all the users, with a mean touch size to be $0.04\,cm^2$ and standard deviation of approximately $0.01\,cm^2$. This analysis shows that typing style, namely the speed and the weight of touch, result in variation of power consumption between $\pm 6\%$ of 1 W. Thus, the different "typing styles" of users do not affect the power consumption of *SK*.

Fig. 4a, as expected shows that, for all input modes the completion time of a message is directly proportional to the message length for all three input modalities. Therefore, it is possible to approximate the message completion times using straight lines with high accuracy ($R^2 = 0.99$). Thus the input speed, s char/s, can be directly obtained as $s = \frac{1}{m}$, where m is the slope of the line presenting the message completion time, the *completion rate*.

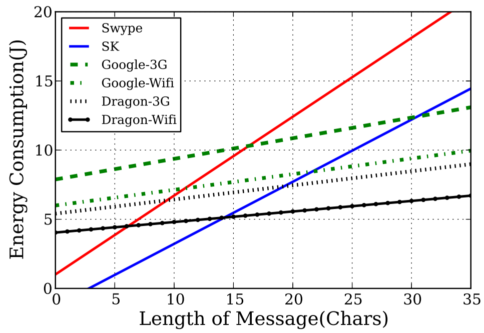
The *completion rate* of *STT* is only $m = 0.074$, when compared to the *completion rates* of *SK* of $m = 0.457$ and *Swype* of $m = 0.422$. This implies that *STT* is up to 6 times faster than that of other two text input modalities, and lead to shorter task completion times. As shown in Fig. 4b, the cross over where *STT* results in faster completion times than *Swype* and *SK* occurs approximately when inputs are 9 and 14 characters respectively.

Fig. 5a shows energy consumption for the three input modalities, which is given by the time taken to complete the task and the average power consumption. It shows that *STT* is more energy efficient than *SK* for longer tasks despite its higher power consumption, as the time taken to complete these task becomes shorter when using *STT* compared to using *SK*. *Google STT* become more energy efficient than *Swype* and *SK* when the message length becomes greater than 16 characters and 30 characters respectively for *Google STT* under 3G. In fact, this is the worst case scenario for *STT* in terms of energy consumption. If user switch to Wifi network or use *Dragon STT*, energy consumption can be cut by almost half, leading to the crossover being 6 chars and 14 chars respectively.

The energy consumption rates from Fig. 5a can be used to derive the percentage of total battery capacity that a user would consume for any particular application that requires text input. TABLE II summarizes the energy consumption of a Samsung Galaxy S3 smart phone for one of the most widely used applications, texting (SMS), considering age-group-based texting statistics provided in [4] as a percentage of the phone battery capacity (7.98WH or 28,728J). It shows that choosing between *SK* and *Swype* may not make much difference in terms of energy consumption, however the use of *STT* could lead to substantial energy savings.



(a) Overall



(b) Zoom in

Fig. 5. Energy consumption comparison of three input modalities

TABLE II
BATTERY CAPACITY OF SAMSUNG S3, 7.98 WH, 28728 J

Age Group	Texts /day	Battery Percentage					
		STT				*SK*	*Swype*
		G_c	G_w	D_c	D_w		
13-17	110	6.21%	4.72%	4.26%	3.18%	9.14%	12.6%
18-24	67.4	3.81%	2.89%	2.61%	1.95%	5.60%	7.73%
24-34	37	2.09%	1.59%	1.43%	1.07%	3.08%	4.24%
35-44	27.7	1.56%	1.19%	1.07%	0.80%	2.30%	3.18%

† G_c, G_w, D_c, D_w stands for Google 3G/wifi, Dragon 3G/wifi.

B. Secondary Experiment Results

1) Device, Battery Charge Level and Networks: The secondary experiments used the Samsung Galaxy S3 used in the primary experiments, a Samsung Galxy S4 and a Google Nexus 7 tablet. They are connected to WiFi and/or 3G cellular networks. The Samsung Galxy S4 represents devices with more powerful hardware and Nexus 7 tablet represents devices with bigger screens and larger batteries. TABLE III presents the energy consumption rates of the three devices for the all input modalities. It shows that the tablet consumes approximately twice as much energy as the S3 per character for all text input modalities. In addition, S4 consumes slightly more energy than S3 mainly due to a higher resolution screen and a faster processor.

Fig. 6 shows the energy consumed by the three devices as a percentage of the device battery, when used for texting by the 13-17 age group. The results show that all devices

TABLE III
ENERGY CONSUMPTION (JOULS/CHAR) OF THE SMARTPHONE AND TABLET

Input Mode	Samsung S3	Samsung S4	Tablet Nexus7
Google-wifi	0.11	0.12	0.27
Dragon-wifi	0.08	0.10	0.19
SK	0.45	0.59	0.87
Swype	0.57	0.61	1.02

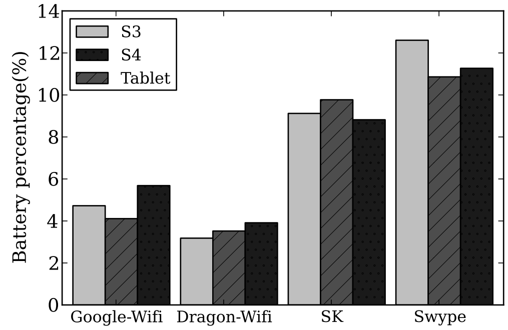


Fig. 6. Battery level consumption for phone and tablet

display similar characteristics despite the tablet consuming twice as much energy per character and the tablet battery having double the capacity (16Wh/57600J) of the S3 battery (7.98Wh/28728J). The S4 battery (9.88Wh/35568J) is around 25% larger than S3's, which is however not always enough to offset the extra power consumption of hardware.

In the case of *STT*, both smart phones display more than double the energy efficiency of the tablet and in the case of *SK*, the tablet performs a bit better battery percentage wise. We speculate that this due the smart phones having more energy efficient communications hardware than tablet.

Since the percentage increase in energy consumption is similar for all the three input modalities across the three devices, the results of previous subsection, namely the differences in energy consumption between the input modalities is device independent.

As *STT* is dependent on sending data to server for analysis, its energy consumption will be influenced by the network connectivity. To assess the impact, we measured the power consumption of *STT* when the smart phone was connected to a 3G cellular network, and a *WiFi* network, in three different locations, namely inside a research laboratory, a residential apartment, and inside a student laboratory at a University. The mean power consumption of *Google STT* in the three locations were all approximately 2 W with a standard deviation under 0.1 W. Hence the results of previous subsection is also location independent.

When the experiment was repeated at a battery charge level of 30%, the power consumption is increased by 5%-10% comparing to when the smart phone was fully charged ($\geq 95\%$). This we believe is due to the non-linear rate of drain of chemical batteries as explained in [29]. However, this again does not affect the main observation as percentage increase in power consumption for all input modalities are similar.

TABLE IV
POWER CONSUMPTION OF LOCATION SERVICE

Input Mode	**S3**	**S4**	**GPS consumption**	
			S3	S4
Google-Wifi-GPS-on	$1.53W$	$1.65W$		
Google-Wifi-GPS-off	$1.29W$	$1.47W$	$0.24W$	$0.18W$
Google-3G-GPS-on	$2.03W$	$2.10W$		
Google-3G-GPS-off	$1.73W$	$1.95W$	$0.30W$	$0.15W$

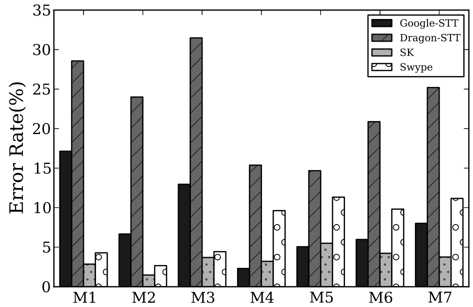


Fig. 7. Error rate for all input modalities

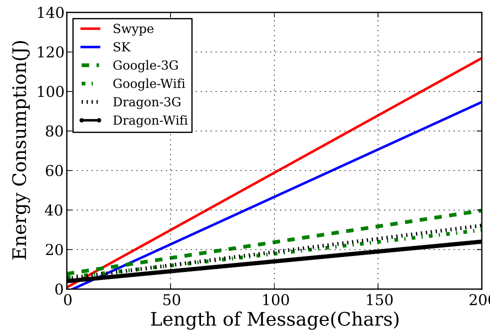
Thus the primary results will remain the same, regardless of the screen size, processing power and battery charge level and will only be influenced by the network type, the application and usage.

2) Location service: Google utilizes location service for *STT* conversion, it is also interesting to know the portion of extra power consumption due to location service and speech streaming respectively. We found almost no difference in terms of power consumption for *Dragon dictation* while keeping the *GPS* module on and off. The *GPS* symbol on the phone also indicates *Google STT* uses *GPS* as oppose to *Dragon dictation*. TABLE IV shows the power consumption of *Google STT* for the two difference smart phone under different network type and *GPS* status. The net power consumption used on location service is deduced, which shows an $0.2W$ is drawn from the *GPS* module on average.

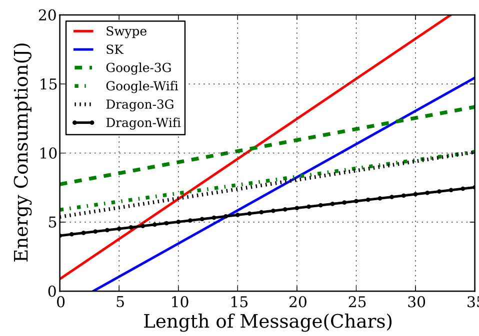
However, the status of location service again would not affect results in primary experiment. Both the results of *Google STT* and *Dragon dictation* are presented, representing upper and lower boundary of *STT* energy consumption. Only slight change in the intersection points is observed, the main trend remains the same.

3) Error Characteristics: *SK*, *Swype* and *STT* display different error characteristics. The *SK* errors are random and evenly distributed (trickle errors), where as the *Swype* and *STT* be word specific and thus tend to occur in groups (burst errors). The two *STT* engines displayed different error behavior. *Google STT* showed higher accuracy (91.69%) when compared to *Dragon dictation* (77.11%) for the set of experiments which consisted of the 7 inputs as shown in Fig. 7. The accuracy was shown to be lower than when using *SK* (96.47%) or *Swype* (92.38%). Also, *Swype* error rate increased with the length of interaction.

Users correct errors differently depending on whether they are using *STT/Swype* or *SK*. Whenever a user makes a mistake when using *SK*, it is generally a single character. Thus the error is corrected by deleting the erroneous character and and enter the correct character. Therefore with *SK*, each error results in 2 key strokes. Therefore, for a message of length L chars, if one assumes an error rate of $e\%$ and that the user will only need to delete the wrong character once, the final length of character input interaction would be $L \times (1 + 2e)\%$. Because overall user's input speed when using *SK* is constant, i.e. that the completion time is linear, error corrected completion time can be derived, the energy consumption calculated.



(a) Overall



(b) Zoom in

Fig. 8. Error Corrected Energy consumption comparison of three input modalities

On the other hand, for *Swype* and *STT*, the prediction engine will underline the words that could be in error. Assuming users take t seconds to press the word and choose the right word a list of words with similar pronunciation, a message length L characters and an error rate $e\%$, the average number of words that need to be corrected can be determined. In turn the extra time, and hence the energy taken to correct all the errors could be determined. Finally, t can be estimated by adding mean press duration from Fig. 3 and thinking/reaction time, where a total number of $500ms$ is used in the calculation.

The results obtained using the above two methods is shown in Fig. 8a. Comparing Fig. 8a with Fig. 5a, the error rates of the different text input modalities do to have a significant impact, and therefore the findings of the primary experiments still hold.

TABLE V
CHARACTERISTICS OF DIFFERENT INPUT MODALITIES

Input Modes	Accuracy	Convenience	Privacy	Speed	Energy Consumption	
					Short	*long*
SK	Highest	Low	High	Fast	Lowest	Low
STT	Lowest	High	Low	Fastest	High	Lowest
Swype	Medium	High	High	Slower	Low	High

V. DISCUSSION

A. Observations

This study has shown that overall, of the three text input modalities that are commonly used, the *SK* has the lowest energy consumption for short interactions. For longer interactions, the *STT* has the lowest energy consumption. Swype on average is the east energy efficient. The results also show that, these findings hold true regardless of the variations in user usage and speaking styles, the type of access network being used, and the type of device that is being used. There is also higher potential for *STT* to have better efficiency gains than SK as the technology improves this will make *STT* the most efficient form of interaction, except for very short interactions (less than 5 characters). Also, it is clear from the finding that, the streaming *Google STT* as opposed "batch" processing *Dragon STT* models have significant energy implications because of the energy overheads of keeping the communication hardware of the mobile device in an active state. The obvious solution is to consider a hybrid approach where "adaptive bundling" is used. This warrants further investigation. Furthermore, *Google STT* utilizes *GPS* module resulting in a 10-20% increased power usage on average, which could be further optimized.

With the current availability of *STT* and *Swype* applications and the trends in text based interactions of smart mobile device users, such as messaging and social media interactions, there will be clear choice for users from solely an energy point of view, as most of these interaction will involve pressing a button, or swiping the screen. However, there are many other factors that will influence users choice of the input modality. TABLE V provides a comparison of what we believe will be the most important of these factors, and provides a subjective assessment of the benefits of *SK*, *STT*, and *Swype* with respect to these factors. When all the factors are taken into account, none of the three input modalities standout as the obvious choice. Therefore it is necessary to develop a recommendation system that takes into account these factors and acts as guide for the users as currently most users are unaware of the implications specially with respect to their battery usage.

B. Limitations

There are potentially a number of limitations of the experiment that were carried out. Firstly, we only considered the input modalities with respect to English. This presents the best case scenario, as *STT* and *Swype* engines are optimized for English. Although it is possible that other languages provide different results, we do not expect major impact on our results by considering English comments only as the language will equally affect all input modalities. Second, the sample sizes and the user population that were used was small. This was necessary because we needed to use the experimental discussed in section III which required the device battery to be "hijacked" to get fine grained energy measurements. We attempted to mitigate this by having users of different nationalities (4 nationalities) and range of age groups (20-50 years) who were regular smart mobile device users. Further we used inputs that are representative of the type of interactions these users would have, from published data. Therefore, despite the sample being small, we do believe that our results are representative. Use of a higher number of users we believe would not significantly lead to significantly different results. Third we only used three devices with a single operating system, *Android*. Despite the differences in the three devices, we could not see any indication that our results were device dependent. As for the operating system, it was not possible to carry out the same set of experiments on *iOS*. We believe this is not a real limitation as the overall findings will be applicable across platforms as the fundamental reasons for the differences stamp from the users, applications and the use of the different hardware components of the smart mobile device. Finally, although, the error rates when using *STT* tend to be higher than when using *SK*, the methodology used provides a fair comparison for two primary reasons. (a) The accuracy of *STT* is improving and (b) the power consumption of *STT* at the longer lengths is significantly lower than that of *SK*. Therefore, overall *STT* will be the most energy efficient at longer lengths (greater than 30 characters).

VI. CONCLUSION

Energy consumption of mobile devices is dependent on the way they are used, because different hardware components of the devices have varying energy demands. As one of the major uses of mobile devices requires text input, and there are different text input modalities, the impact on energy usage when using the different input modalities for text can be significant.

However, determining the implications of different input modalities is difficult as the it is dependent on the user context, the device and the application being used. In this paper we addressed by carrying out a comprehensive energy measurement study of mobile text input under different user context.

The study showed that:

- The most energy efficient input device is different depending on the length of interaction. If the interactions is short, on average less than 30 characters, using the device soft keyboard is the most energy efficient. For longer interactions, the use of a *STT* applications is more energy efficient. *Swype* is more energy efficient than *STT* for very short interactions on average less that 5 characters, but is never as efficient as SK. This is primarily due to *STT* enabling the users to complete tasks more quickly than when using *SK* or *Swype*.

- The above findings are independent of the “user style” and the experience of using any of the input modalities.
- The above findings are also independent of the device characteristics, such as size and manufacturer. This is due to larger devices having larger batteries, and all devices using the components from essentially the same manufacturers.
- The *STT* energy efficiency is dependent on the application logic of whether speech samples are for a given period of time before transmitting to a server for analysis as opposed to streaming the speech to a sever for analysis. It is also affected by the usage of other hardware, *GPS* for instance. Of the two available *STT* engines, Dragon Dictation, which uses the former method with no extra hardware usage, results in reducing power consumption by up to 45%. However, this has the well documented down sides of reduced users *QoE*.

From above it is clear that *STT* energy efficiency can be improved by using a hybrid approach where the speech sample buffering size adaptive: initially very small, but increasing with time to accommodate longer interactions. Hence, additional hardware usage time could be optimized and should not be necessary all the time. With these and the improvements in *STT* accuracy that are taking place, in the future, *STT* will become the most energy efficient text input modality.

In the mean time, users should be recommended to use *SK* for short interactions of less than 30 characters, and *STT* for longer interactions. In addition, they should use *STT* applications which uses storing and transmit logic, if they are willing to trade-off battery life to *QoE*.

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