A Low Power Self-capacitive Touch Sensing Analog Front End with Sparse Multi-touch Detection

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***Abstract*—Capacitive sensing technology is ubiquitous in today's electronic devices. This paper proposes a novel architecture for the design of an ultra low power self-capacitive touch sensing analog front end (AFE) by exploiting the sparsity of simultaneous touches with respect to the number of sensor nodes. It is possible to significantly reduce the complexity and the power consumption of the AFE by migrating the computational burden to the digital processor which usually have surplus computational power. Based on the 1-bit compressive sensing theory, the ADC(s) in the AFE can be replaced by a single comparator. The number of measurements required in order to resolve the touch positions is related to the number of simultaneous touches rather than the number of sensor nodes. Detailed AFE architecture and the capacitance measurement process will be presented along with a corresponding digital reconstruction algorithm run by the digital processor.**

***Index Terms*—1-bit compressive sensing, capacitive touch screen, binary iterative hard thresholding**

I. Introduction

The capacitive sensing technology [1] has been existing for decades. However, it is the launch of iPhone in 2007 that initiated a wave of explosive deployment of the capacitive sensing technology. Today's smart phones are almost unanimously equipped with a capacitive touch screen. There is an increasing demand for capacitive touch screens with larger sizes and quicker responses which implies a higher complexity and power consumption in the analog front end design. However, the number of simultaneous touches supported remains relatively unchanged at the same time. For example, for a capacitive touch keyboard, no more than three key combinations are expected to be entered at the same time. For a phone size screen, one can hardly fit 4 fingers on it. In another word, the ratio between the active touches with regard to the total number of touch sensors is small. The theory of Compressive Sensing (CS) [2] comes into the picture by claiming that the number of measurements required to resolve such kind of sparse signal is approximately proportional to the sparsity of the signal. Reference [3], [4] were among the first few papers that applied the CS concept on capacitive touch screens to exploit the sparsity of simultaneous touches. However, in most cases we are only interested in the locations of the touches rather than its magnitude. Therefore, a precise recovery of the capacitance magnitude is not necessary, which leads to a further simplification of the AFE design. The 1-bit compressive sensing theory [5] fits perfectly into this scenario. This paper proposes a novel architecture for the design of an ultra low power self-capacitive touch sensing AFE based on the concept of 1-bit compressive sensing.

This paper is organized as follows. Section 2 describes a capacitance sensing technique using the charge transfer principle which is adopted in section 3 for the design of a self-capacitance sparse touch sensing AFE. Section 4 presents a reconstruction algorithm run by the digital processor to resolve the touch locations. The performance of the proposed algorithm is justified by two Monte Carlo simulations.

II. Self-capacitance Sensing Principle and Circuit

In electrical circuits, the term capacitance usually refers to the mutual capacitance between two adjacent conductors, such as the two parallel plates of a capacitor. There also exists a property called self capacitance, which is the amount of electrical charge injected onto an isolated conductor to raise its electrical potential by one volt. Theoretically, the reference point for this potential is a hollow conducting sphere of infinite radius, centered on the conductor. In practice, since the earth is a very large conductor and hence is considered to be at zero potential with regard to an isolated conductor, the other plate is considered to be the earth. In a self capacitance touch screen [6], the electrodes can be patterned on a single layer or two layers. Each electrode represents a unique touch coordinate and is connected individually to a controller. As shown in Fig. 1, when a finger or a conductive stylus is close to the electrode, the human body capacitance ΔC is added in parallel with the parasitic or background capacitance $\bar{C}$ of the electrode. A touch is located by sensing the small change in capacitance at that electrode. When the electrodes are laid over two layers, they can be arranged in a layer of columns and a layer of rows such that the (X, Y) coordinate of a touch is determined separately for the row and column.

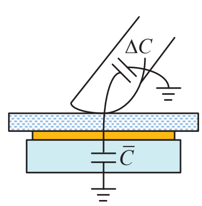

Figure 1. The capacitance change in the presence of a finger.

An accurate and fast capacitance sensing technique lies at the heart of a capacitive touch screen. Also known as "QT"

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sensors, charge transfer capacitance sensors [7] are extremely sensitive and are able to reach a differential resolution of sub-femto (10^{-15}) farads. Figure 2 shows the basic principle of a charge transfer sensing process.

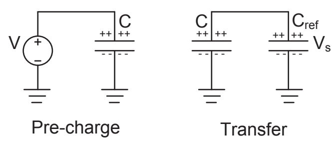

Figure 2. Basic principle of a charge transfer capacitance sensor

In the pre-charge stage, the unknown capacitor C is charged by a DC voltage source V so that in steady state, the charge accumulated over C is

$$Q = VC \tag{1}$$

In the transfer stage, a known reference capacitor C_{ref} is connected in parallel with C such that the charge on C is transferred onto C_{ref}. Denoting the potential over C_{ref} as V_s, according to the conservation of total charge, we have

$$VC = V_s(C + C_{\text{ref}}) \tag{2}$$

which can be rearranged as

$$V_s = \frac{C}{C + C_{\text{ref}}}V. \tag{3}$$

If $C_{\text{ref}} \gg C$, we have

$$V_s \approx \frac{C}{C_{\text{ref}}}V = \frac{1}{C_{\text{ref}}}Q \tag{4}$$

which enables us to estimate the capacitance using a proportional relationship between the drive and sense voltages. Figure 3 shows a practical circuit of a QT sensor. A resistor R_{ref} is connected in parallel with C_{ref} to reset C_{ref} before the next measurement. Switch P is closed during the pre-charge stage, while switch M is open. During the measurement stage, M is closed and P is open. We have

$$V_s(t) = -V\frac{C}{C_{\text{ref}}}e^{-\frac{t}{\tau}}, \tag{5}$$

where $\tau = R_{\text{ref}}C_{\text{ref}}$. At the measurement instant $t = t_0 \ll \tau$,

$$V_s(t_0) \approx -V\frac{C}{C_{\text{ref}}} = -\frac{1}{C_{\text{ref}}}Q, \tag{6}$$

which is exactly the same voltage as in (4) except for a polarity reversal.

III. The Proposed Self-capacitance Sensing AFE Architecture

A. Model Setup

Figure 4 shows a block diagram of the proposed self-capacitance sensing AFE architecture. Suppose there are N capacitance sensor nodes, each of which connects to a MUX. The capacitance at the n-th ($n = 0, ..., N-1$) sensor is

$$C_n = C_n^b + \Delta C_n \tag{7}$$

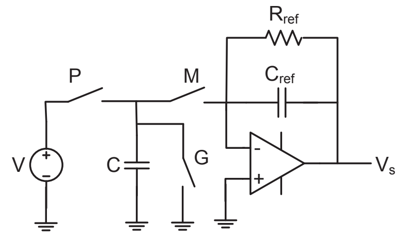

Figure 3. A practical circuit for a charge transfer sensor

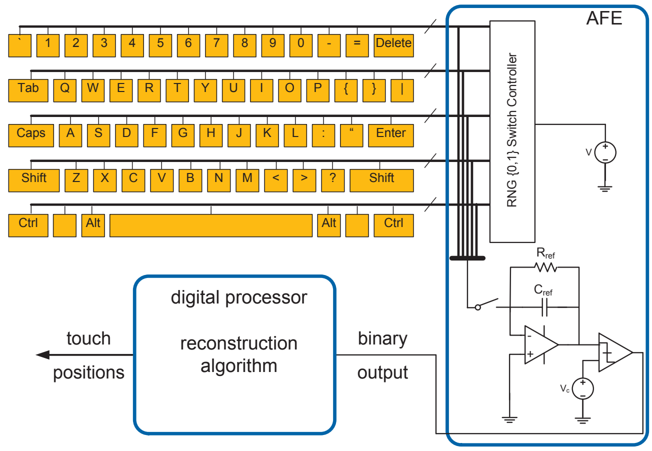

Figure 4. Block diagram of the proposed self-capacitance sensing AFE architecture

where C_n^b is the background capacitance and ΔC_n is the capacitance change introduced by a touch object.

Suppose we will take M measurements. For the m-th ($m = 0, ..., M-1$) measurement, in the pre-charge stage, a Bernoulli random number generator (RNG) will generate a vector of {0, 1} values to control the switch pair P and G to charge each capacitance sensor or not, where "0" indicates that switch P is open and G is closed while "1" indicates that P is closed and G is open. We can denote the charging voltage on capacitance sensor n as V_n^m.

In the sensing stage, all switch P's and G's are open and M's are closed so that all the charge on the capacitance sensor will be transferred to the capacitance measurement circuit as described in Fig. 3. The output of the circuit is

$$V_s^m \approx -\frac{1}{C_{\text{ref}}}Q = \frac{-1}{C_{\text{ref}}}\sum_{n=0}^{N-1} C_n V_n^m. \tag{8}$$

The sensed voltage is then passed into a comparator with a calibration voltage V_c^m, where

$$V_c^m = \frac{-1}{C_{\text{ref}}}\sum_{n=0}^{N-1} C_n^b V_n^m \tag{9}$$

Since the background capacitance C_n^b can be measured offline, we have an exact knowledge of V_c^m. The final binary output of the AFE passed to the digital processor is

$$y^m = \text{sgn}(V_s^m - V_c^m), \tag{10}$$

when combined with (7), (8), (9), we have

$$y^m = \operatorname{sgn}\left(\frac{-1}{C_{\text{ref}}}\sum_{n=0}^{N-1}\Delta C_n V_n^m\right), \tag{11}$$

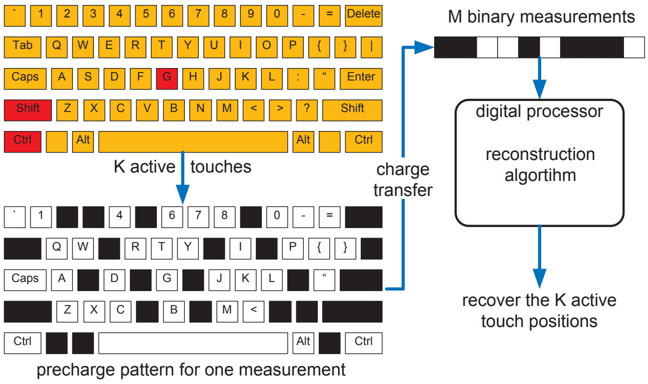

Figure 5. The self-capacitance measurement process with the proposed AFE architecture.

Figure 5 shows a pre-charge, measurement, and reconstruction process. After accumulating M measurements, a reconstruction algorithm will be executed to resolve the positions of the active touches. Denote the capacitance variation vector as

$$\Delta\mathbf{c} = \begin{bmatrix}\Delta C_0 & \cdots & \Delta C_{N-1}\end{bmatrix}^T. \tag{12}$$

Denote the binary output vector of the AFE as

$$\Delta\mathbf{y} = \begin{bmatrix}y^0 & \cdots & y^{M-1}\end{bmatrix}^T. \tag{13}$$

Denote the Bernoulli distributed pre-charge matrix as

$$\mathbf{\Phi} = \frac{-1}{C_{\text{ref}}}\begin{bmatrix} V_0^0 & \cdots & V_{N-1}^0 \\ \vdots & \ddots & \vdots \\ V_0^{M-1} & \cdots & V_{N-1}^{M-1}\end{bmatrix}. \tag{14}$$

In matrix form, (11) can be written as

$$\mathbf{y} = \operatorname{sgn}(\mathbf{\Phi}\Delta\mathbf{c}) \tag{15}$$

The remaining question is how do we resolve the position of the non-zero entries in $\Delta\mathbf{c}$ from $\mathbf{y}$.

B. Reconstruction Algorithm

The data acquisition model in (15) was first introduced in [5] in 2008. In our proposed model, $\Delta\mathbf{c}$ is a sparse vector with only K ($K \ll N$) non-zero values according to the sparse simultaneous touch assumption. The reconstruction of $\Delta\mathbf{c}$ can be formulated as

$$\min \|\mathbf{x}\|_1 \quad s.t. \quad \mathbf{y} = \operatorname{sgn}(\mathbf{\Phi}\mathbf{x}) \tag{16}$$

Note that if $\hat{\mathbf{x}}$ is an optimal solution in (16), then any positive scaling of $\hat{\mathbf{x}}$ is also an optimal solution. In another word, we cannot reconstruct the magnitude of the signal with the sensing model. However, in our touch sensing model, the exact magnitude of $\Delta\mathbf{c}$ is not important. We are only interested in the non-zero positions in $\Delta\mathbf{c}$ which correspond to the touch locations. Therefore, we can add an additional constraint $\|\mathbf{x}\|_2 = 1$ to make (16) yield a unique solution and locate the non-zero positions in the optimal solution $\hat{\mathbf{x}}$. To get rid of the non-linear operator sgn, we can define a diagonal matrix

$$\mathbf{Y} = \operatorname{diag}(\mathbf{y}). \tag{17}$$

(16) can be reformulated as

$$\min \|\mathbf{x}\|_1 \quad s.t. \quad \mathbf{Y}\mathbf{\Phi}\mathbf{x} \geq 0, \quad \|\mathbf{x}\|_2 = 1 \tag{18}$$

A geometrical view of the principle of the 1-bit compressive sensing scheme is shown in Fig. 6.

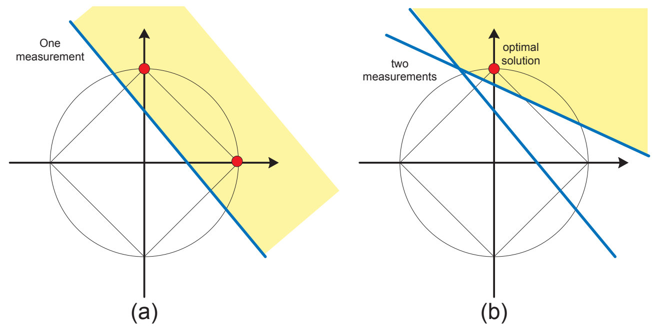

Figure 6. A geometrical interpretation of the 1-bit compressive sensing scheme. (a) one measurement (b) two measurments

Each binary measurement defines a hyperplane which confine the optimal solution in one of the two subspaces divided by the hyperplane. The hyperplane has a random orientation due to the randomized projection matrix $\mathbf{\Phi}$. As shown in Fig. 6(a), with only one measurement, the optimal solution can not be unambiguously determined. Due to the randomness of the hyperplane orientation, we will have a high probability of confining the solution subspace so that there is only one optimal solution in the subspace once we have enough measurements. As shown for the case in Fig. 6(b), we can uniquely determine the optimal solution with two measurements.

A number of algorithms has been proposed to solve (18) such as matching sign pursuit [8], and restricted-step shrinkage [9], among which the binary iterative hard thresholding(BIHT) [10] algorithm offers the best robustness. BIHT is a simple modification of iterative hard thresholding (IHT) [11] which solves the problem

$$\min \|\mathbf{y} - \mathbf{\Phi}\mathbf{x}\|_2 \quad s.t. \quad \|\mathbf{x}\|_0 = K. \tag{19}$$

We further customize the BIHT algorithm to monitor only the support of the solution in each iteration. The customized algorithm is summarized in Algorithm 1. Line 3 calculates the gradient $\frac{1}{2}\mathbf{\Phi}^T(\mathbf{y} - \operatorname{sgn}(\mathbf{\Phi}\mathbf{x}^j))$ at $\mathbf{x}^j$ and moves $\mathbf{x}^j$ towards the direction of the gradient with a step size τ. The function $f_K(\cdot)$ keeps the K largest entries in terms of magnitude and zero-out the rest of the entries. The iteration stops when the support or the non-zero locations of $\mathbf{x}^{j+1}$ remains the same as the previous iteration.

Algorithm 1: A customized BIHT algorithm

Inputs: Pre-charge matrix $\mathbf{\Phi}$, binary measurements $\mathbf{y}$, multi-touch support K, step size τ

Output: Non-zero locations of $\Delta\mathbf{c}$

Initialization:

$\mathbf{x}^0 = \mathbf{0}$

Iteration:

repeat

$\quad \mathbf{z}^{j+1} = \mathbf{x}^j + \frac{\tau}{2}\mathbf{\Phi}^T(\mathbf{y} - \text{sgn}(\mathbf{\Phi}\mathbf{x}^j))$

$\quad \mathbf{x}^{j+1} = f_K(\mathbf{z}^{j+1})$

$\quad j = j + 1$

until $\mathit{supp}(\mathbf{x}^{j+1}) == \mathit{supp}(\mathbf{x}^j)$;

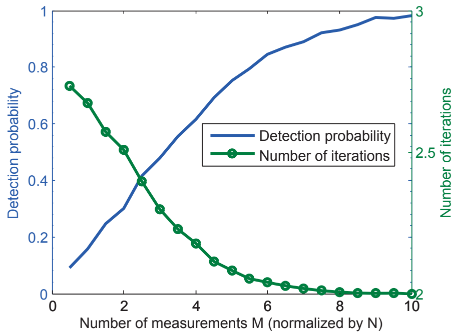

Figure 7. The touch detection probability and number of iterations as a function of the number of measurements.

Figure 7 shows a Monte Carlo simulation with the capacitance sensing model and the customized reconstruction algorithm. Every points on the figure is averaged over 1000 experiments. We assume a $N = 16*9 = 144$ button touch pad with $K = 3$ multi-touch support. The capacitance variation $\Delta\mathbf{c}$ is assumed to be uniformly distributed in [0, 1] at K randomly picked locations. A successful detection means that the exact K touch locations are resolved. The number of measurements M varies from $0.5N$ to $10N$ with infinite SNR. The detection probability of the K multi-touches increases as we obtain more measurements while the number of iterations for the proposed algorithm to converge decreases. With more measurements, we will have a smaller solution subspace bounded by the measurement hyperplanes. Therefore, we would have a higher probability of locating the optimal solution in the subspace and it takes the algorithm less iterations to converge to the optimal solution. On the other hand, more measurements means more power consumption and longer data acquisition time with the AFE and more computations in the digital reconstruction algorithm. Tradeoffs must be made between the AFE power consumption and acceptable detection probability by determining the optimal number of measurements.

Figure 8 shows a Monte Carlo simulation with variable signal SNRs. The setups are exactly the same as in Fig. 7 with zero mean additive Gaussian noises applied to the measurements. The detection probability increases as we take more

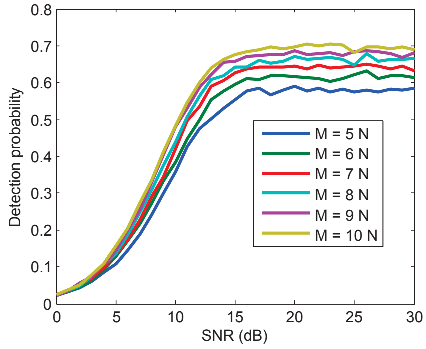

Figure 8. The touch detection probability as a function of the signal SNR.

measurements or have a higher SNR.

IV. Conclusions

This paper presents a novel architecture for the design of an ultra low power self-capacitive touch sensing analog front end by exploiting the sparsity of simultaneous touches with respect to the number of sensor nodes. The proposed AFE is significantly simplified compared with the standard AFE design which requires one or multi-channel ADCs. The number of measurements required in order to resolve the touch positions is related to the number of simultaneous touches rather than the number of sensor nodes. The touch positions will be resolved by a recovery algorithm in the digital domain.

References

[1] R.B. Mudit and V.B. Anand, "Comparative study of various touchscreen technologies," *International Journal of Computer Applications*, vol. 6, no. 8, pp. 12–18, Sep. 2010.

[2] E.J. Candes and T. Tao, "Near-optimal signal recovery from random projections: Universal encoding strategies?," *Information Theory, IEEE Transactions on*, vol. 52, no. 12, pp. 5406 –5425, Dec. 2006.

[3] Chenchi Luo, J. McClellan, M. Borkar, and A. Redfern, "Sparse touch sensing for capacitive touch screens," in *Acoustics, Speech and Signal Processing (ICASSP), 2012 IEEE International Conference on*, May 2012, pp. 2545–2548.

[4] Chenchi Luo, M.A. Borkar, A.J. Redfern, and J.H. McClellan, "Compressive sensing for sparse touch detection on capacitive touch screens," *Emerging and Selected Topics in Circuits and Systems, IEEE Journal on*, vol. 2, no. 3, pp. 639–648, Sep. 2012.

[5] P.T. Boufounos and R.G. Baraniuk, "1-bit compressive sensing," in *Information Sciences and Systems, 2008. CISS 2008. 42nd Annual Conference on*, 2008, pp. 16–21.

[6] G. Barret and R. Omote, "Projected-capacitive touch technology," *Information Display*, vol. 26, no. 3, pp. 16–21, Mar. 2010.

[7] H. Philipp, "Charge transfer sensing," *Sensor Review*, vol. 13, no. 11, pp. 96–105, May 1999.

[8] P.T. Boufounos, "Greedy sparse signal reconstruction from sign measurements," in *Signals, Systems and Computers, 2009 Conference Record of the Forty-Third Asilomar Conference on*, 2009, pp. 1305–1309.

[9] J.N. Laska, Zaiwen Wen, Wotao Yin, and R.G. Baraniuk, "Trust, but verify: Fast and accurate signal recovery from 1-bit compressive measurements," *Signal Processing, IEEE Transactions on*, vol. 59, no. 11, pp. 5289–5301, 2011.

[10] L. Jacques, J.N. Laska, P.T. Boufounos, and R.G. Baraniuk, "Robust 1-bit compressive sensing via binary stable embeddings of sparse vectors," *Information Theory, IEEE Transactions on*, vol. 59, no. 4, pp. 2082–2102, Apr. 2013.

[11] T. Blumensath, M. Yaghoobi, and M.E. Davies, "Iterative hard thresholding and l0 regularisation," in *Acoustics, Speech and Signal Processing, 2007. ICASSP 2007. IEEE International Conference on*, 2007, vol. 3, pp. 877–880.