Design Considerations for Mems Devices

Mantha Anil Srimanth, Kameshwara Rao SA, Perna Kishor Krishna, Arra Ashok

M. Tech, Department of ECE, Sreenidhi Institute of Science & Technology
B. Tech
M.TECH, Department of ECE, Sreenidhi Institute of Science and Technology
M.TECH, Department of ECE, Sreenidhi Institute of Science and Technology,

Abstract: *The market of the consumer electronics, automobiles is now taken over by MEMS. MEMS or Microsystems technology or Micromachined Devices is a technology where micro-level electro-mechanical elements are fabricated, in which there exists no physical movement of mechanical parts to the more complex electromechanical systems. These also contain a micro level sensors and actuators which have the mechanical motion inside the chip.*

I.   Introduction

MEMS (Microelectro Mechanical Systems), it defines mechanical structures fabricated with IC processing on silicon wafers, also labeled Microsystems and Micromachines. MEMS-based devices play a valuable and instrumental role in the sensor world, in their application in the measurement of physical variables.
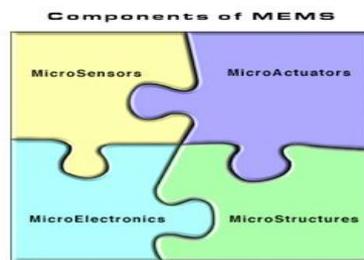
Figure-1: Components of MEMS

Key MEMS sensors include the following principles:
• Pressure
• Acceleration
• Rate
• Force

Pressure sensors were the first devices based on silicon technology introduced to the market in the 1960s, for military and aerospace applications. In the year 2003, the volume of pressure sensors produced approached 200 million units, with automotive and markets dominating the unit volume.

Acceleration and gyro MEMS-based sensors were developed for military and aerospace market in the 1970s. In the year 2003, over 100 million units were produced and it was dominated by the automotive airbag applications. MEMS rate sensors were developed in the 1990s, first for military, and then for automotive applications.

The emerging MEMS sensing applications include the following:
• Infrared
• Flow
• Chemical
• Biological
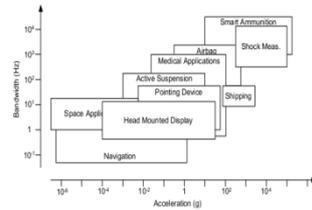
Figure-2:The application areas for accelerometers and the bandwidth-resolution performances of the accelerometers for these applications

Major sensing technologies that can be applied in the MEMS include the following:
• Piezoresistive
• Capacitive
• Resonant
• Thermoelectric

The piezoresistive effect in silicon produces resistance change that is approximately 2 orders of magnitude larger when compared to the change that would result from a dimension change under applied stress (typical for metals). For example, if the material is elongated 0.1% by stretching, typical metallic resistors used for strain gauges would change by about 0.2%, but the resistance of silicon would change by about 10%. Piezoresistive sensors dominate pressure, acceleration, and force applications. Typically, four piezoresistors are connected into a Wheatstone bridge configuration to reduce temperature errors.

Capacitive sensors have at least one electrode moving under the input variable, which typically would be pressure, acceleration, or rate. While the simplest configuration is two flat electrode capacitors, the interdigitated silicon fingers, gained wide acceptance as an inertial sensor, as it allows for larger sensing capacitance.

Resonant sensors are based on resonating beams or diaphragms. Applied strain changes the resonant frequency (similar to a guitar string), enabling measurement of input variables such as pressure, acceleration, rate, and temperature. Resonant frequency pickup may use any of the sensing technologies.

MEMS thermoelectric sensors are based on a large number of tiny thermocouples connected in series. These are primarily used to measure IR radiation. One end of the thermocouple is located over a thermally isolated region of the chip, the other end over conducting silicon. In response to radiation, the thermally isolated end of the thermocouple gets warmer, enabling measurement of IR power. The merging approach for both chemical and biological MEMS sensors are based on carbon nanotube technology, demonstrated by Silicon Valley compares; it has great potential for creating new markets for yet more MEMS sensors.

Application Area	Uses	Range	Bias Stability
Navigation	Aircraft Spacecraft/Satellite Land Cruise Missile	200 deg/sec	0.01-0.1 deg/hr
Tactile Missiles	Air-to-surface Air-to-land Air-to-surface	200 deg/sec	0.1-100 deg/hour
Automotive	Navigation Airbags ABS/TCS Active suspension	100 deg/sec	0.001-1 deg/sec
Medical and Consumer electronics	Microsurgery Camcorders Robotics	10-100 deg/sec	0.1 deg/sec

Table-1: Range and bias stability requirements for gyroscopes for different applications.

II. Literature Survey

MEMS defines the technology; not specific products. This technology encompasses a collection of a variety of processes enabling three-dimensional shaping of wafers or stacks of wafers. While most of the applications use silicon wafers, many other materials have been used, including glass and quartz wafers. MEMS based devices play a valuable and instrumental role in the sensor world, in their application in the measurement of physical variables. Key MEMS sensors include Pressure,

Acceleration, Rate, Force sensors. Major sensing technologies that can be applied in the MEMS form include the following piezoresistive, capacitive, resonant and thermoelectric.

Starting from metal diaphragm sensors with bonded silicon strain gauges, and moving to present developments of surface-micromachined, optical, resonant, and smart pressure sensors. Considerations for diaphragm design are discussed in detail, as well as additional considerations for capacitive and piezoresistive devices, results from surface-micromachined pressure sensors are developed.

BRAIN-CONTROLLED INTERFACES

Brain-controlled interfaces are devices that capture brain transmissions involved in a subject's intention to act, with the potential to restore communication and movement to those who are immobilized. Current devices record electrical activity from the scalp, on the surface of the brain, and within the cerebral cortex. These signals are being translated to command signals driving prosthetic limbs and computer displays. Somatosensory feedback is being added to this control as generated behaviors become more complex. New technology to engineer the tissue-electrode interface, electrode design, and extraction algorithms to transform the recorded signal to movement will help translate exciting laboratory demonstrations to patient practice in the near future.

Neural prosthetics are devices that link machines to the nervous system for the purpose of restoring lost function. Two broad approaches are used in this field: neurons are stimulated or inhibited by applied current, or their activity is recorded to intercept motor intention. Stimulation can be used for its therapeutic efficacy, as in deep brain stimulation to ameliorate the symptoms of Parkinson's disease or to communicate input to the nervous system (for example by transforming sound to neural input with cochlear prosthetics). In contrast, recordings are used to decode ongoing activity for use as a command or input signal to an external device. Capturing motor intention and executing the desired movement form the basis of brain-controlled interfaces (BCI), a subset of neural prosthetics used to decode intention in order to restore motor ability or communication to impaired individuals.

Every BCI has four broad components: recording of neural activity; extraction of the intended action from that activity; generation of the desired action with prosthetic effectors; and feedback, either through intact sensation, such as vision, or generated and applied by the prosthetic device.

III.   Recording Technology

The first step in the BCI process is to capture signals containing information about the subject's intended movement. While researchers have envisioned using methods based on either magnetic or electromagnetic signals from the brain, these devices are not yet practical for BCI use. Currently, the four primary recording modalities are electroencephalography (EEG), electrocorticography (ECoG), local field potentials (LFPs), and single-neuron action potential recordings (single units). All of these methods record microvolt-level extracellular potentials generated by neurons in the cortical layers. The methods are classified by whether the electrodes are placed on the scalp, dura, cortical surface, or in the parenchyma, and by the spatial and spectral frequency of their recorded signals. Generally, there is a tradeoff between these parameters; the more invasive the recording technique, the higher the spatial/spectral frequency content of the recorded signal which, in turn, depends on the current densities conducted through the volume of the head. The primary current sources and sinks, i.e., where current enters the cell and leaves the cell, respectively, are synapses (both excitatory and inhibitory) and the voltage-sensitive gates underlying neuronal action potentials. Because most nonspherical neurons are oriented radially, these currents approximate a dipole source, which contains both equal and opposite polarities, oriented perpendicular to the cortical surface. Taken as a whole, the cortex can be modeled as a thin, convoluted sheet of aligned dipoles whose individual magnitudes vary continuously in time. BCI recording aims to sample this dipole sheet and extract the desired control signal.
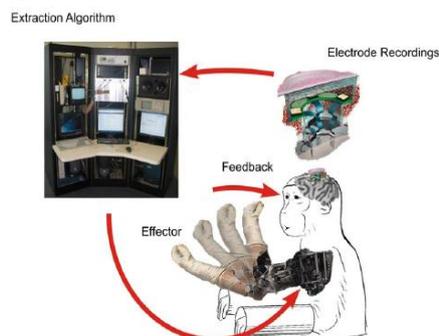
Figure-3: BCI Recording Technology

From a purely engineering point of view, the optimal method of recording this electrical information would be to place a series of small electrodes directly into the dipole sheet to intercept signals from individual neurons (single-unit BCI designs). The ability of a microelectrode to record single-unit action potentials depends on many factors, such as electrode impedance, tip size and shape, whether the target cell has an open or closed extracellular field, and the size and orientation of the target neuron. Layer V cells in the motor cortex have the

largest cell bodies in the cerebrum (>100 mm) and generate large electrical fields, making them an ideal source for extracellular recording. Multisite silicon probes can record distinguishable spikes from layer V neurons in rat sensorimotor cortex located more than 300 mm away in the axial direction, although this distance is likely smaller in the tangential direction. At this spatial resolution, the potentials due to local synaptic currents are negligible compared to the electric potentials created by an action potential. These signals are usually band-pass filtered from 300 to 10,000 Hz and then passed through a spike discriminator to measure spike time occurrences. The firing rates of individual neurons are computed in 10–20 ms bins and ''decoded'' to provide a high-fidelity prediction of either computer cursor or robot endpoint kinematics. Given its high spatial resolution (100 mm) as well as its high temporal resolution (50–100 Hz), this modality arguably provides the highest level of control in BCI applications. One problem with this technique is that, once the electrodes penetrate the parenchyma, they are susceptible to a number of failure modes.

Alternatively, recent work using ECoG and LFPs suggests that some spike-related activity can be extracted by looking at higher frequencies and that this signal may provide reasonable BCI control.

We can differentiate between five main recordable signals representing certain spatial resolutions.

(1) Mass activity is measured either by electrodes sitting outside the head on the skin (EEG)

(2) By electrodes sitting on the brain surface (epicortical ECoG). EEG signals are recorded within a spatial domain of 3cm whereas epicortical ECoG electrode grids used in human epilepsy diagnosis have spatial resolution of about 5 mm.

(3) Microelectrodes used in an epicortical ECoG recording are able to measure local field potentials (LFP) in a spatial domain of 0.1 mm. LFPs can be recorded from the brain's surface as well as from electrodes penetrating the brain tissue measuring intracortically.

(4) Multi unit activity (MUA)

(5) Single unit activity (SUA) is measured intracortically with a microelectrode inserted into the tissue.

Single-Unit Activity (SUA)

The term single-unit refers to a single neuron. A single-unit activity is the signal of a discharging neuron which is intracortically measured by a microelectrode. The electrode picks up all signals generated in the vicinity (100 μm) of the tip. The largest signals originate from the large pyramidal cells of layer V which have a cell body size of about 10-30 μm. After high-pass filtering the signal at >300 Hz, neurons can be distinguished from others by their signal shape. By spike detection and sorting, each spike signal is assigned to its corresponding neuron. SUA is a digital signal. It tells whether a neuron is firing or not. Thus, the information is not contained in the signal amplitude but in the firing rate. As the microelectrode measures only in a small volume close to a neuron, the largest signal it records is the change in the extracellular potential field of the nearest cell. This signal is larger in amplitude and shorter in signal duration (1-2 ms) than the signals described below. The firing rate of a single, well isolated neuron has been the main parameter used in systems neuroscience for decades. As the extracellular fluid has low-pass filter properties, SUA is a strong signal only locally, and is attenuated rapidly over the distance some micrometers away from the electrode tip.

Multi-Unit Activity (MUA)

Like SUA, MUA is recorded by an intracortical electrode. Using an electrode with low impedance 40-120 kΩ and placing it further away from the large, spike generating cells, the signal is not dominated by the activity of one principal neuron. Within a sphere around the electrode tip having a radius of 50-350 μm, signals are recorded that consists of spikes coming from multiple neurons as well as from dendrite activity. By high-pass filtering this compound signal, a weighted sum of action potentials from all neurons in the recorded volume is obtained. The weighing of the different action potentials is given by the distance between each neuron and the electrode site.

Local Field Potential (LFP)

If the same compound signal is low-pass filtered, one obtains a LFP. Compared to SUA and MUA, the LFP is an analogue signal. It is the summation signal of dendritic potentials that are presenting the input signals of the cells. Thus the LFP is an averaged measure of pre- and postsynaptic activity within a volume of neuronal tissue whereas SUA and MUA show single action potentials of large pyramidal cells. Postsynaptic potentials have a signal duration of 10-250 ms, and by overlapping lead to synchronic activity that can be measured To eliminate the high-frequency components of single spikes, the signal is low-pass filtered <300 Hz. LFPs appear to convey relevant information that is not present in neuronal spike activity such as attention or predicting the time of a planned movement. In addition, LFP fluctuations are also closely correlated with hemodynamic changes measured by fMRI and underlie the generation of EEG and MEG measurements. LFPs can either be measured with an intracortical or with an epicortical electrode.

Mass Activity

According to its name, the mass activity is a summation signal reflecting the activity of a large neuronal population. As the LFP, mass activity exhibits average properties and does not represent single neuron activity or interconnections. If signals are recorded non-invasively on the scalp, they are very small due to the attenuation taking place between the cortex surface and the scalp. Thus only the synchronized activity of a large group of neurons is possible to record. An area of several square millimeters or even centimeters of synchronized cortical tissue is needed to generate a measurable voltage in the mV range on the scalp. Mass activity can also be recorded by epicortical electrodes. Compared to intracortical microelectrodes, they have a relatively large electrode area and low impedance. The position on the cortical surface instead of inserting them into the cortex results in a placement further away from the large cortical neurons. Thus, the recorded signals consist more of dendrite activity than single neuron action potentials.

Extraction Algorithms

Extraction algorithms can be categorized broadly into inferential methods and classifiers. Empirically derived models are the basis for inferential methods and include the population vector, optimal estimators, and linear and nonlinear filters. Classifiers require no basic understanding of the relation between neural activity and behavior, relying instead on consistent patterns within and between variables and include self organizing feature maps, back-propagation, and maximum-likelihood methods.

Filter techniques take into account the current and historic state of the ongoing movement, using motor variables that vary in a regular and predictable way. During the time-varying process underlying a motor act, this state model is combined with instantaneous neural activity to update the predicted movement. Development of more sophisticated state space models will likely enhance cortical prosthetic control. Another important factor in the success of any extraction method is how well the subject can learn to use the algorithm. It may turn out that a simple approach, using, for instance, the population vector algorithm, may be just as, or more, powerful than more elaborate approaches. The demonstrated learning that takes place with these algorithms in closed-loop algorithms is responsible for an increased performance with fewer recorded units.

Learning, manifest as feedback-dependent changes in neural activity, serves an important role in achieving high performance with brain-controlled interfaces. So far, the feedback signal has only been visual—for instance, a monkey may watch a computer display or robot arm and make online corrections to the movement or improve the cosine fit of the neural activity recorded with the chronic electrodes. Again, as prosthetic complexity increases, somatosensory input will become more important.

IV.   Conclusion & Future Scope

The interdisciplinary nature of MEMS relies on design, engineering and manufacturing expertise from a wide and diverse range of technical areas including integrated circuit fabrication technology, mechanical engineering, materials science, electrical engineering, chemistry and chemical engineering, as well as fluid engineering, optics, instrumentation and packaging. The complexity of MEMS is also seen in the extensive range of markets and applications that incorporate such devices.

MEMS can be found in systems ranging from consumer electronics, automotive, medical, communication to defence applications. Current examples of MEMS devices include accelerometers for airbag sensors, microphones, projection display chips, blood and tire pressure sensors, optical switches, and analyticalcomponents such as lab-on-chip, biosensors and many other products.

Thus there is a rapid growth for the MEMS technology. As the biomems are proposed hardly there are a handful of models that can be incorporated into the brain controlled interfaces. There are only a few neuron models proposed till date as the research is going on since decades there is no unique model that can be interfaced to mems devices and can be used as a bioimplant. Hence in future a neuron model can be proposed that can be used as a brain interface device.

References

[1]   Piezoresistive Effect in Germanium and Silicon Smith, C.S. Piezoresistive Effect in Germanium and Silicon. Physical Review , 94, 42–49.

[2]   Barlian, A. Alvin, W-T. Park, Joseph R. Mallon, Ali J. Rastegar, and Beth L. Pruitt. "Review: Semiconductor piezoresistance for microsystems."Proceedings of the IEEE 97, no. 3 (2009): 513-552.

[3]   Hong, Jia-sheng. "Reconfigurable planar filters." Microwave Magazine, IEEE 10, no. 6 (2009): 73-83.

[4]   Verger, Aurélie, Arnaud Pothier, Cyril Guines, Aurelian Crunteanu, Pierre Blondy, Jean-Christophe Orlianges, J. Dhennin, F. Courtade, and Olivier Vendier. "Sub-hundred nanosecond reconfiguration capabilities of nanogap RF MEMS switched capacitor." In Microwave Symposium Digest (MTT), 2010 IEEE MTT-S International, pp. 1238-1241. IEEE, 2010.

[5]   Di, Si, Hui Lin, and Ruxu Du. "An artificial compound eyes imaging system based on MEMS technology." In Robotics and Biomimetics (ROBIO), 2009 IEEE International Conference on, pp. 13-18. IEEE, 2009.

[6]   Miao, P., P. D. Mitcheson, A. S. Holmes, E. M. Yeatman, T. C. Green, and B. H. Stark. "MEMS inertial power generators for biomedical applications."Microsystem Technologies 12, no. 10-11 (2006): 1079-1083

[7]   Polymer-Based Micro implants for the Neurosciences   Birthe Rubehn   Dissertation zur Erlangung des Doktorgrades der Technischen Fakultät der Albert-Ludwigs-Universität Freiburg im Breisgau Oktober 2010.

[8]   Cohen, Michael X., Nikolai Axmacher, Doris Lenartz, Christian E. Elger, Volker Sturm, and Thomas E. Schlaepfer. "Nuclei accumbens phase synchrony predicts decision-making reversals following negative feedback." The Journal of Neuroscience 29, no. 23 (2009): 7591-7598.

[9]   Te Lindert, B. H., and E. J. Van Someren. "Sleep Estimates Using Microelectromechanical Systems (MEMS)." Sleep 36, no. 5 (2012): 781-789.

[10]   Schwartz, Andrew B., X. Tracy Cui, Douglas J. Weber, and Daniel W. Moran. "Brain-controlled interfaces: movement restoration with neural prosthetics."Neuron 52, no. 1 (2006): 205-220.

[11]   Tsytsarev, Vassiliy, Makoto Taketani, Frank Schottler, Shigeru Tanaka, and Masahiko Hara. "A new planar multielectrode array: recording from a rat auditory cortex." Journal of neural engineering 3, no. 4 (2006): 293.

[12]   Waldert, Stephan, Tobias Pistohl, Christoph Braun, Tonio Ball, Ad Aertsen, and Carsten Mehring. "A review on directional information in neural signals for brain-machine interfaces." Journal of Physiology-Paris 103, no. 3 (2009): 244-254.

[13]   Rubehn, Birthe, Conrado Bosman, Robert Oostenveld, Pascal Fries, and Thomas Stieglitz. "A MEMS-based flexible multichannel ECoGelectrode array." Journal of neural engineering 6, no. 3 (2009): 036003.

[14]   Stieglitz, Thomas, Birthe Rubehn, Christian Henle, Sebastian Kisban, Stanislav Herwik, Patrick Ruther, and Martin Schuettler. "Brain–computer interfaces: an overview of the hardware to record neural signals from the cortex." Progress in brain research 175 (2009): 297-315.

[15]   Bosman, Conrado A., Jan-Mathijs Schoffelen, Nicolas Brunet, Robert Oostenveld, Andre M. Bastos, Thilo Womelsdorf, Birthe Rubehn, Thomas Stieglitz, Peter De Weerd, and Pascal Fries. "Attentional stimulus selection through selective synchronization between monkey visual areas." Neuron 75, no. 5 (2012): 875-888.