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Sleeping Laboratory: Intelligent Glass And Sensor Technology In Real Time Medical Environment.

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***Abstract:** Sleep studies are used to evaluate and diagnose a variety of sleep problems. A sleep study is very potential in controlling neurological, breathing and movement disorders. Some of the problems that may lead doctor to order a sleep study are snoring, sleep apnea, sleep walking, bedwetting, sleep talking, the feeling of being tired all day, sleeping during a day. A sleeping laboratory can detect these interruptions, analyse and record detailed information to help doctor diagnose problem and determine the best treatment. Light therapies and simulation of day-night environment have been recognized that can stabilize the patterns of delayed sleep phase syndrome and advanced sleep phase syndrome. In this paper we present sleeping laboratory based on smart glass controlled automatically by sensors, ccd camera and real-time pattern recognition environment. We present sensor network and real-time multiparametric algorithms sending signals to intelligent glass controller. For classification we used fast SVM classifier with new kernel method. Historical medical database is used as training set for automated classifier.*

Introduction

The right amount and quality of sleep is essential to human well-being. As sleeping problems are affecting about 30% of the population, new approaches for everyday sleep measurement are needed (4). It has been estimated that about 30% of the population have the symptoms of insomnia, the most prevalent sleep disorder (26).Another sleep disorder with major health effects, sleep apnea, has a prevalence of 3% – 8% in men (depending on the population sample) and 2% in women in the most affected age group of 40 to 65 years (26). Obesity significantly increases the risk of sleep apnea (8). With overweight increasing globally (27), sleep apnea will become more and more prevalent. According to estimates about 40% of the adult population in western cultures is affected by problems with falling asleep or daytime sleepiness (11).

Sleep is a physiologic phenomenon that is controlled by the central nervous system (CNS). Rapid eye movement sleep (REM) was discovered in 1953 (1), which established the still-valid classification of CNS activity into three fundamentally distinct states: REM sleep, non-REM sleep (NREM) and wakefulness. As already tested, exogenous administration of the pineal hormone melatonin by night simulation may be a promising treatment for improving sleep (e.g. Lerner and Case 1960; Rollag and Niswender 1975) (21, 28).

Some studies suggest that melatonin exerts a sleep promoting effect only when endogenous melatonin levels are low (i.e. during the daytime), whereas when endogenous levels are high (i.e. at night), exogenous melatonin may not produce substantial effects (Dawson and Encel 1993;

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Stone et al. 2000) (7). Studies of melatonin administered to promote night-time sleep, however, have produced mostly negative results (e.g. Dawson and Encel 1993; James et al. 1987; Stone et al. 2000) (13, 29).

Sleep lab studies can help evaluate and diagnose a variety of sleep problems. The established practice of medical sleep monitoring, polysomnography, involves wearing multiple electrophysiological sensors for a single night, at a sleep laboratory or at home (12). It provides clinically valuable information, but is expensive because patient must be monitor over several nights.

The unobtrusive sleep measurement in artificial night environment makes it possible to monitor patients with sleep problems in shorter time in their normal sleeping cycles. The awareness of the circadian order to selective phase shifting by timed light exposure has expansive indications for the treatment of sleep-phase and depressive disorders. In recent years a number of consumer products have appeared that aim at solving sleep related problems (14).

The use of electronically trigger, variable transmission materials, and prediction control methods in hospitals and care centres can enhance environmentally and medical sustainable behaviors. Today, active materials and artificial intelligence methods, promise to add new direction to windows, including the real time transformation of their light transparency and their performance, based on given settings.

Electrochromic windows (2, 3, 24, 33) are made of special materials that have electrochromic parameters. Electrochromic describes materials that can adjust color when energized by an electrical current. For instance, by actively controlling the state of electrochromic glass panes, the daily light transmittance of windows grow into a programmable component, by which it is available to regulate the interior illuminance and temperature (10, 19).
The transitions of intelligent windows, optimally managed, can supply to the control of light transmission and room temperature. Electrochromic equipment technology is based on chemical reactions whereas Suspended Particle Devices technology needs field effects. These technologies are extensively proposed to manufacture intelligent windows (17). These types of glass can be automatically managed to ad-just the amount of light glancing through them. Adaptable by managed and sesnors variable-tint electrochromic (EC) windows preserve the view out while modulating transmitted light, glare, and solar heat gains and can reduce energy use and peak demand. Prior building energy simulation studies indicated that electrochromic windows have the technical potential also in medicine. Some of these studies (primarily conducted in the 1980s to early 1990s) have estimated that electrochromic windows can influence on temperature, heating in buildings situated in moderate to climates (with warming effect) if combined with daylighting controls that dim the electric lighting in response to daylight (e.g., Sullivan et al. 1994, Lee and Selkowitz 1995) (20, 30).

Classification + RealTime + Databases

The combination of this information with real time answer from sensors (building and patient) enables the rearrangement of the facade, even in settings that cannot be foreseen by the static simulation model. The overall system resolves two complementary intentions: 1) determines the optimum electrochromic glass transparency to scope the desired interior temperature and illuminance level, and 2) bounds the current window patterns to this threshold. In last 10 years, the application of multiparametric classifiers to remote-sensing and image sensors has been seriously investigated.

A new type of classifiers, the Support Vector Machines, has been introduced within the framework of the Statistical Learning Theory (31, 32) developed by V. Vapnik and co-

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workers. In praxis, the SVM has been tested to optical character recognition, speech recognition, image processing, handwritten digit recognition and text categorization. One problem that faces the user of an SVM is how to determine a kernel and the individual parameters for that kernel. Implementations of an SVM accordingly desire a search for the optimum settings for a specific data situation. Because these are among the considerable sensor systems from which database store information is derived, an evaluation of the performance of the SVM using texts and images from such sensor systems should have practical implications for classification. The purpose of this paper is to demonstrate the applicability of new fast kernel method for sleeping lab sensor systems and systematically to evaluate its performances in comparison to other popular kernel methods used by SVM. In sleeping lab project, we developed customized Kernel method for a linear support vector machine (SVM) to detect in real-time patient sleeping profiles which allow then to stimulate room environment.

Decision and Visualization

In order to simplify a data preparation for visual analysis, pre-processing and post-processing steps should be simple and should not require programming knowledge. We suggest to implements the interactive method in workflow systems which is crucial for enabling users to deal with data pre-processing and post-processing. The concept of workflow is not new and it has been used by many organizations, over the years, to improve productivity and increase efficiency on data preparation (16, 34). Long-term sleep measurement allows new possibilities for improving sleep, which in turn has positive health effects. We have identified in this paper two primary means of such sleep improvement: patter recognition of sleep and sleep measurement environment as part of medical sleep disorder treatment. Sleepiness, performance, and mood during the sleeping screening experiments in this project were evaluated using the multiple sleep latency test (MSLT) and a sensor environment connected to centralized database system.

Methods

The camera and sensors pick up forces caused by face mimics, heartbeats, respiration, and movements, so those physiological parameters can be measured. Based on the parameters, the quality and quantity of sleep is analysed and send signals to glass controller. The sensor system is a fully automated real-time environment for sleep monitoring in the room with intelligent glass environment. The novelty of the approach is that the sleep information produced by unobtrusive measurement is send to the window controller, which then control light and day-night environment.

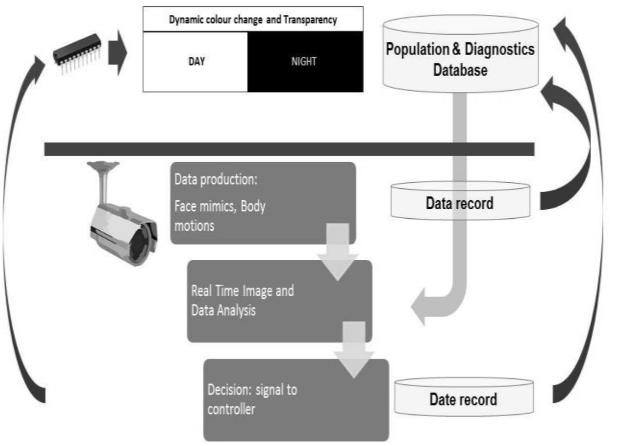

Figure 1. Intelligent glass technology in medicine.

Glass technology

We use electrochromic technology which basically characterizes materials that can adjust color while energized by an electrical current. Electricity cause a chemical reaction in this substance. This reaction modifies the properties of the material. In this special case, the reaction adjusts the way the material reflects and absorbs light. In some other electrochromic materials, the change is between different colors. In electrochromic glass, the material changes

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between colored (reflecting light of some color) and transparent (not reflecting any light). Windows are normally glazed or coated in some transparent or translucent material like float.

Electrochromic glass is built by sandwiching certain materials between two panels of glass. Figure 2 shows the materials inside one basic electrochromic glass system and the way in which this system works. In the scheme presented in Figure 2, the chemical reaction at work is an oxidation reaction – a reaction in which molecules in a compound lose an electron. Ions in the sandwiched electrochromic layer are what grant it to change from translucent to transparent. It's these ions that allow it to absorb light. A power source is wired to the two regulated oxide layers, and a voltage drives the ions from the ion storage layer, through the ion conducting layer and into the electrochromic layer. This makes the glass opaque. By switching off the voltage, the ions are pushed out of the electrochromic layers and into the ion depot layer. When the ions leave the electrochromic layer, the window recovers its transparency. With an electrochromic smart-window, it only requires electricity to make the initial change in opacity. Managing a special shade does not require constant voltage. One only needs to apply enough voltage to make the change, and then sufficient to reverse the change. Electrochromic glass has been implemented at laboratories of HTG Glass company.

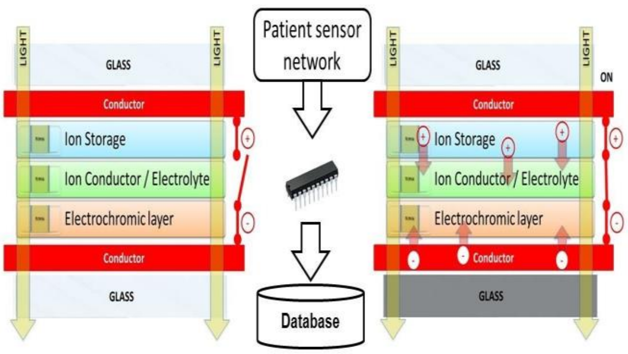

Figure 2: Electrochromic glass layers. Controller

The smart control system of the building exploits the passive thermal capacity of the house envelope. Illuminance in daylight conditions is subject to constant adjustment of intensity and distribution. Room daylight is affected by the patient sensors and movement of the sun and of the clouds. The conditions regulating the optimum daylight vary based on the daytime and month of the year. The existing simulation models for sleeping lab provide a poor account of daylight modification. These models identify and approximate uncomplicated settings, which do not reproduce the natural sunlight conditions.

The windows are controlled in a concerted manner by the central control without having autonomous intelligence capability. The controller was implemented in C++. The hardware hosting the controller is a standard computer with 16GB of RAM, SSID HDD and Intel Double Core i7 processor. The controller also manages illumination and humidity.

Fast SVM

We use for this machine learning methods. A sensor intelligent model is adaptively inferred from the signal using a classification algorithm, and the model is utilized in detecting heartbeat intervals, respiration, movements, face mimics, humidity, indoor temperature, outdoor temperature, sun illumination, calendar data, cloud transparency, indoor voice signals.

The support vector machine (SVM) is one of the outstanding methods to sensor data analysis. In *supervised classification* we have a set of data samples (each consisting of measurements on a set of variables) with associated labels, the class types (day, night). These are used as exemplars in the classifier design. The classification experiments in sleeping lab were carried out with a support vector machine (SVM) [ref]. Discriminative approaches to recognition problems often depend on comparing distributions of parameters,
e.g. a kernelized SVM, where the kernel measures the similarity between histograms describing the

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features. In many practical cases where performance of classification is significant SVM with standard kernel function like Gaussian Kernel (GK) or Radial Basis Function (RBF) are not suitable.

Currently, the use of kernels in learning algorithms has received consideration. The main argumentation is that kernels allow mapping the data into a high dimensional feature space in order to increase the computational power of linear machines (see for example Vapnik, 1995, 1998, Cristianini and Shawe-Taylor, 2000) (5, 6).

SVM can be optimized for performance via the kernel methods adapted for medical sensor network. In Kernel algorithms, the initial observations are effectively mapped into a higher dimensional non-linear space. For a given nonlinear mapping ϕ, the input data space X can be mapped into the feature space H:

$$\phi : X \to H \;\; where \; x \to x : \phi(x). \tag{1}$$

Linear classification in this non-linear space is then equivalent to non-linear classification in the original space. Require Fisher LDA can be rewritten in terms of dot product.

$$K(x_i, x_j) = \phi(x_i) \bullet \phi(x_j) \tag{2}$$

Unlike Support Vector Machine (SVM) it doesn't seem the dual problem declare the kernelized problem naturally. But animated by the SVM case we make the following key assumption,

$$w = \sum_i \alpha_i \phi(x_i) \tag{3}$$

In terms of new vector α the objective $J(\alpha)$ becomes,

$$\arg\max_{\alpha \in R^n} J(\alpha) = \frac{\alpha^T S_B^{\phi} \alpha}{\alpha^T S_W^{\phi} \alpha} \tag{4}$$

Table 1 presnts most popular kernel methods.

Table 1. Most popular kernels used for SVM classification.

Kernels	Formula
Linear	K(x, x')= x. x'
Sigmoid	K(x, x') = tanh(a x. x'+b)
Polynomial	K(x, x') = (1+ x. x')^d
RBF	K(x, x') = exp(-γ || x - x'||^2)
Gaussian	K(x, x') = exp(-γ || x - x'||)

Therefore, a pattern in the original input space R^n is mapped into a possibly much higher dimensional feature vector in the feature space H. The scatter matrices in kernel space can expressed in terms of the kernel only as follows:

$$S_{\mathbf{B}}^{\phi} = [K_1 K_1^T - KK^T] + [K_2 K_2^T - KK^T] \tag{5}$$

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$$S_W^{\phi} = K^2 - (N_1 K_1 K_1^T + N_2 K_2 K_2^T) \tag{6}$$

$$K_1 = \frac{1}{N_1} \sum_{im \in psoitive} K_{im} , K_2 = \frac{1}{N_2} \sum_{i,m \in negative} K_{im} \tag{7}$$

$$K = \frac{1}{N} \sum_{i,j \in N} K_{ij} \tag{8}$$

Attractive choice is the Gaussian kernel

$$K(i,j) = \exp(-\frac{\| i-j \|^2}{2\sigma^2}) \tag{9}$$

with a suitable width of kernel and must σ > 0.

Note that since the objective in terms of α has exactly the same form as that in terms of w.

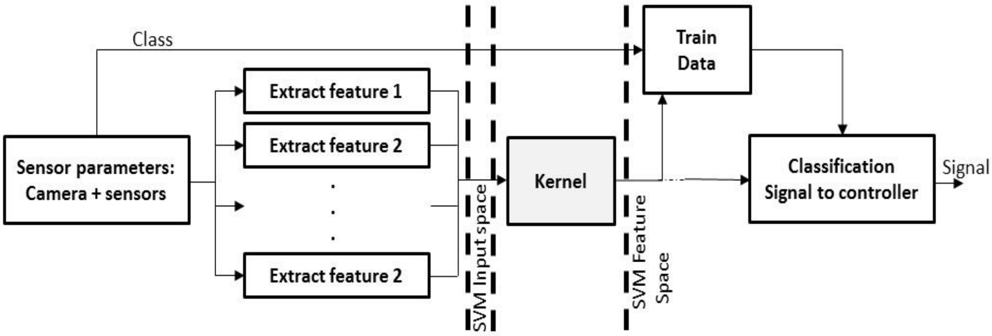

Figure 3. Classification model.

In this project the input raw medical sensor data is not directly deliver into SVM as inputs. Instead, a set of simple features is first obtained from raw data, and then the features are used as inputs. It will be assumed that each sensor observation z = $\{b_1, \ldots, b_M\}$ is composed of a set of range-bearing measures $b_i = (\alpha_i, d_i)$ where α_i and d_i are the bearing and range measures, respectively. Each training set for the SVM method is composed by one observation z_i and its classification υ_i. The set of training examples is then given by

$$E = \{(\mathbf{z}i, \upsilon i) : \upsilon i \in Y = \{day, night, \ldots\}\} \tag{10}$$

where Y is the set of classes. In this paper it is assumed that the classes of the training examples are given in advance (night, morning, noon, afternoon, evening, night). The objective is to learn a classification system that is able to observe from these training data and that can later classify day/night in laboratory environment.

Kernel SVMs have become popular for real-time applications as they enjoy both faster training and classification speeds, with significantly less memory requirements than non-linear kernels due to the compact representation of the decision function (35).

The crossplane kernel, K_{HI} (t_a, t_b) = n_i=1 min (t_a(i), t_b(i)) is often used as a measurement of similarity between histograms t_a and t_b, and because it is positive definite (25) it can be used as a kernel for discriminative classification using SVMs. Recently, crossplane kernel SVMs (call CPSVMs), have been

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shown to be successful for detection and recognition (9, 18). We based on kernel Intersection Kernel (35). Given feature vectors (parameters from sensors) of dimension n and learned support vector classifier consisting of m support vectors, the time complexity for classification and space complexity for storing the support vectors of a standard CPSVM classifier is T (p u). We apply an algorithm for CPSVM classification with time complexity T (u log p) and space complexity T(pu). We then use an approximation scheme whose time and space complexity is T (u), independent of the number of support vectors. The key idea is that for a class of kernels including the crossplane kernel, the classifier can be decomposed as a sum of functions, one for each histogram bin, each of which can be efficiently computed. In sleeping lab screens with thousands of support vectors we also observe speedups up to 2000× and 200× respectively, compared to a standard implementation.

We want demonstrate that it is feasible to improve performance of CPSVMs. For feature vectors x, z ∈ R_{+}^{n}, the crossplane kernel is:

$$K(x,z): K(x,z) = \sum_{i=1}^{n} \min(x(i), z(i)) \quad (11)$$

and classification is based on evaluating:

$$h(x) = a_0 + \sum_{l=1}^{m} \alpha_l y_l K(x, x_l) + b = \sum_{l=1}^{m} \alpha_l y_l (\sum_{i=1}^{n} min\,(x(i), x_l(i))) + b \quad (12)$$

Thus the complexity of assessment h(x) in the naive way is O(pu). The maneuver for crossplane kernels is that we can convert the summations in equation 7 to obtain:

$$h(x) = \sum_{l=1}^{m} \alpha_l y_l (\sum_{i=1}^{n} min\,(x(i), x_l(i))) + b \quad (13)$$

$$= \sum_{i=1}^{n} (\sum_{l=1}^{m} \alpha_l y_l min\,(x(i), x_l(i))) + b$$

$$= \sum_{i=1}^{n} \ h_i(x(i)) + \mathrm{b}$$

Rewriting the function h(x) as the sum of the particular functions, h_i, one for each dimension, where

$$h_i(s) = \sum_{l=1}^{m} \alpha_l y_l \min(s, x_l(i)) \quad (14)$$

Up to now we have gained nothing as the complexity of computing each $h_i(s)$ is T(p) with an overall complexity of computing h(x) still T(pu). We now demonstrate how to calculate each h_i in T(logp) time. Consider the functions $h_i(s)$ for a fixed value of i. Let $\bar{x}_l(i)$ denote the sorted values of $x_l(i)$ in rising order with corresponding α' s and labels as $\bar{\alpha}_l$ and $\bar{y}_l$. If $s < \bar{x}_1(i)$ then $h_i(s) = 0$, if not let r be the largest integer such that $\bar{x}_r(i) \leq s$. Then we have,

$$h_i(s) = \sum_{l=1}^{m} \bar{\alpha}_l \bar{y}_l \min(s, \bar{x}_l(i)) \quad (15)$$

$$= \sum_{1 \le l \le r} \bar{\alpha}_l \bar{y}_l \bar{x}_l(\mathrm{i}) + \mathrm{s} \sum_{r \le l \le m} \bar{\alpha}_l \bar{y}_l$$

$$= A_i(r) + sB_i(r)$$

Where we have defined,

$$A_i(r) = \sum_{1 \le l \le r} \bar{\alpha}_l \bar{y}_l \bar{x}_l(\mathrm{i}), \quad (16)$$

$$B_i(r) = \sum_{r \le l \le m} \bar{\alpha}_l \bar{y}_l \quad (17)$$

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Equation 17 shows that hi is piecewise linear. Moreover h_i is continuous as long as:

$$h_i(\bar{x}_{r+1}) = A_i(r) + \bar{x}_{r+1}B_i(r) = A_i(r+1) + \bar{x}_{r+1}B_i(r+1). \quad (18)$$

Consider that the functions A_i and B_i are independent of the input data and depend only on the support vectors and α. Hence, if we precompute $h_i(\bar{x}_r)$ then $h_i(s)$ can be computed by first finding r, the position of s = x(i) in the sorted list $\bar{x}$ (i) using binary search and linearly interpolating between $h_i(\bar{x}_r)$ and $h_i(\bar{x}_r+1)$. This requires storing the $\bar{x}_l$ as well as the $h_i(\bar{x}_l)$ or twice the storage of the standard implementation. Thus the runtime complexity of computing h(x) is T(u logp) as opposed to T(pu), a speed up of T(u/logp). In our experiments we normally have SVMs with a few thousand support vectors and the resulting speedup is quite significant.

Results:

BigData Visualization

The primary use case for the sleep measurement system is a interactive data visualization application by which doctors may monitor their sleep and make discoveries about their sleep and lifestyle. Sleep information is presented so that the relevant features of sleep can be detected easily.

The basic idea of interactive visualization is to provide the data in one visual frame that allow users to gain insight into the data and generate hypotheses by directly interacting with image data. The advantage of interactive visualization is that users are directly involved in the image processing results to combine the flexibility, creativity, and general knowledge of the scientist with the enormous amount of numerical rows connected to image files. This tool is developed to help scientists, answer complex queries through interactive visual exploration of screening data sets. One key attribute of the interactive visualization that distinguishes it from past and current image data explorations methodologies is that the original image data, their image processing results and metadata (additional information captured by acquisition software about an image, such as the instruments used, camera, acquisition settings, image size, resolution) are link together and available for filtering, clustering in interactive view.

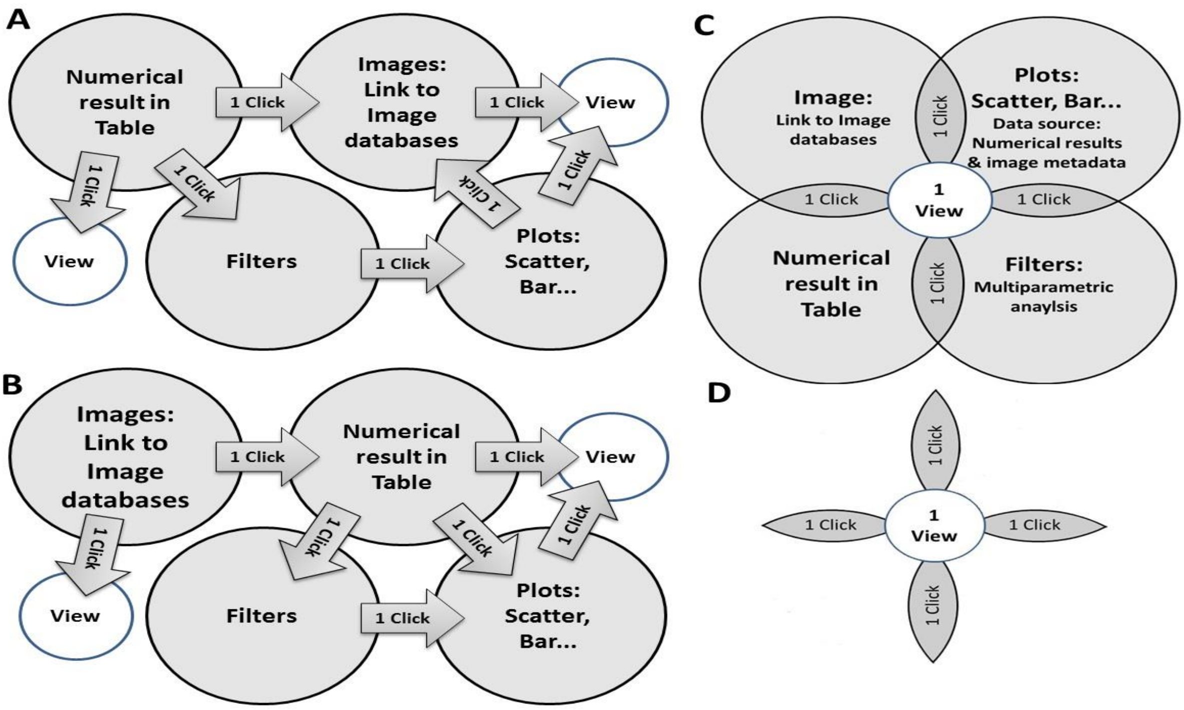

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Figure 2: A and B – traditional analytics scenarios for image based data sets. Multiple clicks and distributed views. C. Interactive method: use one view and with one click scientist should get access to all related data sources and analytical tools: images, plots, numerical results, filters. The concept is focus to reduce number of clicks – access to all information should be direct and user actions should minimized with maximum of interactions. D. Star model as software methodology for interactive visualization tools. (Image source 34)

Algorithm and Visualization

In order to demonstrate the effectiveness and classification precision of our algorithm we performed a series of tests on standard benchmark data sets. Data sets are presented in table 1. We tested a proposed extension of Intersection Kernel in experimental datasets from two patients. We use the standard SVM algorithm for binary classification already presented. The regularization factor of SVM was fixed to $C = 10$. In order to see the response of observation performance on the size of training data set and model complexity, experiments were carried out by varying the number of training samples (50, 150, 300, 350, 465) according to a 5-fold cross validation assessment of the generalization error. The data was split into training and test sets and normalized to minimum and maximum feature values (Min-Max) or standard deviation (Std-Dev).

Table 1: Sensor dataset (sleeping lab). Time stamps are done every 10 second. Experiment duration 4 hours.

	Total	Training data	Test data
Time stamps	1440	7,220	7,220
Wake-up	460	230	230
	(8%)		
Sleep	980	465	465

Table 2. Classification results for two datasets from two patients using two kernel methods with c = 30.

Dataset 1:

Training set	Kernel RBF	Training Time/ Classification Time	Classification Accuracy	Intersection Kernel	Training Time/ Classification Time	Classification Accuracy
50	C = 10	14 s / 3s	84.6%±5.7	C = 10	10 s /2s	85.7%±1.6
150	C = 10	24 s / 7s	85.1%±1.6	C = 10	14 s / 5s	84.5%±5.7
300	C = 10	32 s / 11s	83.1%±3.5	C = 10	21 s / 11s	87.2%±2.5
350	C = 10	40 s / 15s	86.2%±2.5	C = 10	26 s / 12s	87.3%±3.3
465	C = 10	44 s / 18s	84.3%±2.9	C = 10	31 s / 15s	83.6%±3.5

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Dataset 2:

Training set	Kernel RBF	Training Time/ Classification Time	Classification Accuracy	Intersection Kernel	Training Time/ Classification Time	Classification Accuracy
50	C = 10	13 s / 3s	86.6%±6.7	C = 10	11 s /3s	85.4%±2.6
150	C = 10	26 s / 8s	84.3%±2.5	C = 10	14 s / 4s	83.9%±6.5
300	C = 10	30 s / 10s	84.0%±4.4	C = 10	22 s / 12s	88.1%±1.6
350	C = 10	39 s / 14s	84.1%±1.5	C = 10	25 s / 13s	86.2%±2.4
465	C = 10	43 s / 17s	84.5%±2.7	C = 10	32 s / 16s	83.8%±2.6

Results for our classifier are presented in table 2. The RBF kernel is slower for SVMs than intersection kernel SVMs, because the time is dominated by the evaluation of the SVM. We achieve 1/3 of speed using intersection kernel over RBF kernel. File I/O times vary from 0.4 seconds for Dataset 1 to about 3 seconds for Dataset 2. For dataset 2, the intersection kernel is also better than RBF.

Implementation: Among the various software applicable to implement SVMs, for our experiments we applied the software SVMlight designed by T. Joachims (15). The experiments have been carried out on a Windows 8.1 operating system. In this project, we used the NVIDIA 7700 GTX GPU GeForce, which is an instance of the G100 GPU design, and is a standard GPU widely available on the market. The training phase of a single two-class classifier of each SVM (for a given kernel and a given value of the parameter C), using the patterns of one of the five classes as positive examples (labelled P) and the others as negative examples (labelled N), usually took less than one minute.

Conclusion

This article highlighted the use of electrochromic glass in smart windows, i.e., windows that can be adjusted to modulate the amount of light entering a sleeping laboratory. The proposed micro-controlling technique for electrochromic windows is based on training an SVM using a supervised learning approach. A set of body motion, face mimics, eyes features, extracted from a body sensors and CCD camera are fed into the SVM and used for classification, possible in real time. We presented the impacts of kernel method used in SVM configuration on the performance of the SVM and of the selection of training data and input variables on the RBF kernel were also evaluated in this experiment. In terms of algorithm stability, we proved that intersection kernel used for SVM gave more stable overall accuracies than the RBF Kernel except when trained using to short time distance between measurements. Compared to RBF SVM and speedup methods our experiments showed a very competitive speedup while achieving reasonable classification results. Especially if our initial assumption holds, that large problems can be split in mainly easy and only a few hard problems, our algorithm achieves very good results. The advantage of this approach clearly lies in its simplicity since no parameter has to be tuned. Experiments carried out with real sensor data demonstrate the feasibility and effectiveness of intelligent glass technology and machine learning techniques for medical application.

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