e[m]erge work report 2

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1 Introduction

This report describes developments in the *e[m]erge* project as of the end of May, 2012.

2 Data analysis

In our context, the goal of data analysis is to determine useful ways to look at sensor data such that it can be fed into a dynamic system in order to generate responses.

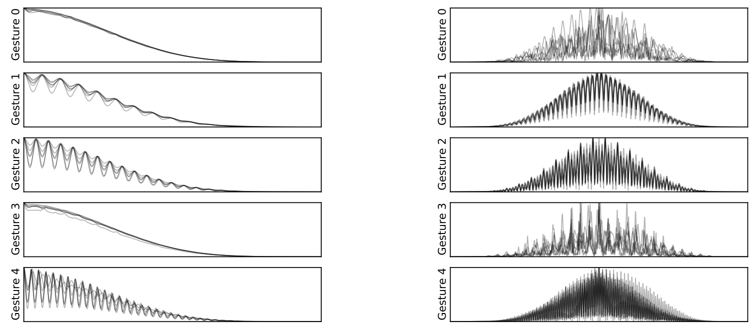
An interpretation of "useful" here is that analysis should well-characterise variations in the data such that interesting features can be extracted. In other words, we wish to perform dimensionality reduction, however we also make use of standard supervised classification techniques in order to evaluate the ability of reduced featuresets to predict data tags. If prediction is good, we can estimate that some combination of features is "useful" for a dynamic system to respond to, and likely, for driving media content.

Therefore we stress that classification is not the end goal of this analysis, however it is a tool for examining the predictive quality of features that we estimate from the raw data. In this report we additionally use unsupervised methods for visual inspection of separability in a severely reduced number of dimensions.

2.1 Workshop 1 data

The data from Workshop 1 was described and evaluated in the previous report. It consisted of subjects with accelerometers performing guided gestures that might be typical of a concert environment. The session was video taped and this was post-analysed to "tag" the data with gesture information.

However, these tags were relatively unstructured and not every subject was necessarily following the instructions at every frame. Analysis was successful in separating low- and high-energy gestures. More nuanced separation was not successful during analysis, possibly due to a low sample rate of only approximately 10 Hz.



a) b)

Figure 1: (a) Example magnitude autocorrelation vectors of lab data set separated by subject and gesture. (b) Example magnitude inter-axis correlation vectors of lab data set separated by subject and gesture.

In the future we would like to revisit this data set using techniques described in the following section, which may perhaps yield more success, but as of the time of writing this has not yet been done. On the other hand, if sample rate is indeed a problem as we suspect, new data should be recorded.

2.2 Lab data

Six subjects were asked to perform five distinct gestures while holding a Minibee wireless accelerometer. A black dot was moved around on the screen, and the subjects were asked to follow it with their hand, causing periodic or random motion of various patterns. The accelerometer was held in the fist. This exercise provided us with pre-tagged data under a controlled environment, which could subsequently be used as a basis for evaluating data analysis methods.

Initial investigation by comparing autocorrelation of the accelerometer magnitude showed that gestures were mostly distinct, and that there was some similarity between subjects. Fig. 1a overlays one autocorrelation vector for each subject and gesture, separated by gesture.

Use of magnitude autocorrelation as a feature for ANN prediction, seen in Fig. 2, resulted in classification that was not completely satisfactory. Although classification was successful for some gestures, several gestures just barely classified.

However, taking the magnitude of accelerometer data necessitates throwing out useful information about orientation. On the other hand, calculating orientation explicitly has its own problems: it requires removing of the gravity bias, and orientation can be represented in several ways, requiring some choices.

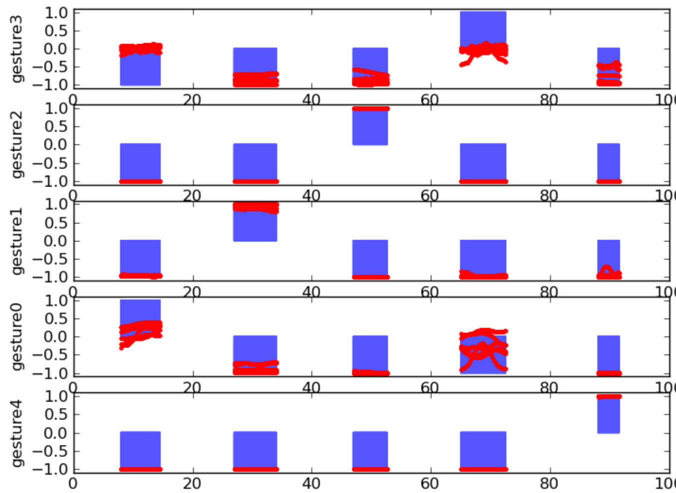


Figure 2: ANN classification results using magnitude autocorrelation.

2.2.1 Inter-axis correlation analysis

We decided that it would be more productive to attempt a more general analysis method that takes into account rotation without explicitly representing it. The idea is to calculate the correlation between the three rotation axes and take the sum of their absolute values. This inter-axis correlation views the three accelerometer axes as separate sensors and considers merely their mutual covariance. A high-pass filter is used to remove gravity bias.

Other than this pre-filtering, this method is effectively agnostic to specific information abou the sensor, therefore we hope it can be used e.g. between sensors connected to kinematically-related bodies, or even different types of sensors. It is possible that summing the correlation vectors is also unnecessary, and the whole set of three correlation vectors could be used, however we found the sum to be an effective method of combining the correlations.

Results are shown in Fig. 1b. It can be seen that there is more variation between the gestures, yet agreement across subjects is still quite good. These results were also evaluated as classification features, Fig. 3. It is clear that classification has been improved.

2.2.2 Data reduction

Unfortunately these correlations provide very large feature vectors, which would represent large amounts of data for exchange, and likely impact real-time performance. Currently we are using a 10-second buffer at 100 Hz, or 1024 points,

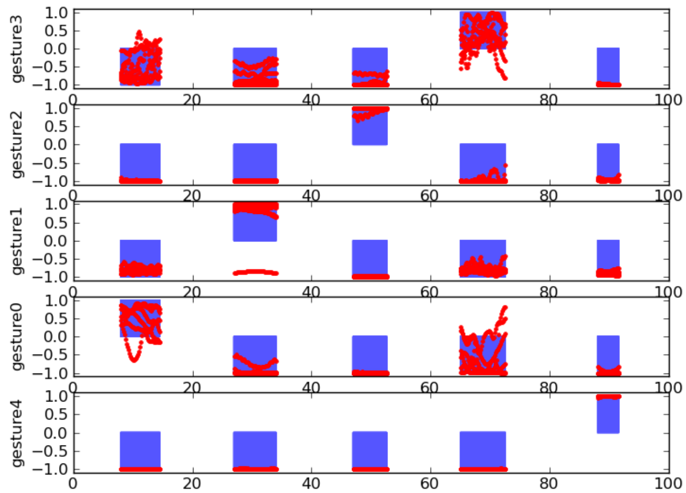


Figure 3: ANN classification results using inter-axis correlation.

generating a correlation vector of 2048 points. Per sensor, this could amount to a large amount of data to process.

We prefer to reduce the data to salient axes, giving two advantages: 1) Less data to transfer during real-time performance; 2) data reduction can be performed on sending nodes, reducing the processing requirement of the dynamic system host.

An initial attempt was based on the observation that the correlation vectors tend to have a periodic structure. This structure was "summarized" by calculating some standard features used in periodic waveform analysis. The fast Fourier transform (FFT) of the correlation vectors was calculated, and the spectral centroid and slope were calculated according to standard formulae.

These two values were then used as features in classification, giving results seen in Fig. 4. Although some misclassifications are obvious, the results are still superior to those of the magnitude autocorrelation, with most data being correctly classified.

2.2.3 Instantaneous correlation

Another method that was evaluated is the instantaneous correlation. Since correlations may need to be performed locally on sensor nodes, we sought a more efficient means of characterising sensor streams in an online scenario. In particular, the correlation methods described above require processing a sliding window of 1024 samples. Of course, different window sizes can be chosen, however the method of instantaneous correlation described in [1] replaces this

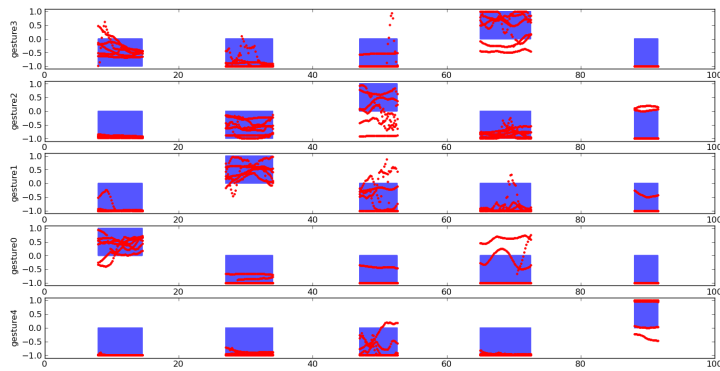


Figure 4: ANN classification results using a reduced representation of the inter-axis correlation.

window with an exponential forgetting factor. This allows efficient calculation of correlation using an IIR filter representation. Running several such filters at different delays allows the construction of a 2D correlation matrix.

Examples of such matrixes generated from the lab data can be found in Fig. 5. These images were made with a 200 delays, and a filter cut-off selected at 5 Hz.

It can be seen that each gesture generates a distinct pattern. Therefore this method shows promise in identifying gestures. Unfortunately, since the forgetting factor emphasises recent data above old data, it leads to a "sliding" behaviour in the characteristic pattern over time. This makes the use of this data for recognition at any particular time slice difficult. Moreover, at mistuned cut-off frequencies, we found that this pattern was much less distinct, therefore tuning is an important consideration for using this method.

We tried using such vectors as classification features but this did not perform well, presumably due to the time-varying nature. We also tried using the FFT of the instantaneous correlation vector and comparing only the magnitude, so as to ignore phase information, but this did not yield greater success.

Therefore, we conclude that more research is needed to make use of instantaneous correlation, however there are indications that it could be worth pursuing since it lends itself well to real-time constraints and smaller memory loads.

2.2.4 Principal component analysis

Principal component analysis (PCA) can be used to identify "why" and "whether" certain feature sets may provide good separation. This can be viewed as an alternative method to using classification to evaluate feature sets. It is considered an unsupervised learning method in the sense that the data is used to determine a transformation to a more useful representation, without reference to external

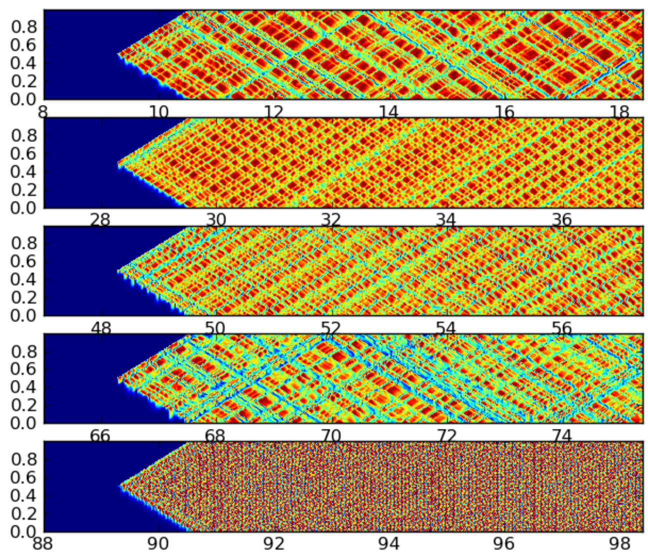


Figure 5: 2-D instantaneous correlation of lab data at 5 Hz.

information such as tags.

Some unsupervised techniques such as k-means analysis perform clustering, however PCA merely determines a change in coordinates such that a new "view" on the data maximally spreads out the variance in the new coordinate system. In the sense that it should reduce data to a minimal number of salient dimensions, it can be considered an optimal way to view data in a reduced number of dimensions. Thus, by plotting the first two principal components, we may see how much variance is in the data on a 2-D graph.

This result is given in Fig. 6. In Fig. 6a, the two first PCs of each gesture is plotted, coloured by gesture, and we can see that each gesture tends towards its own part of the space. Thus we can say that this data is separable. On the other hand, in Fig. 6b, the same lines are coloured by subject, and it is noticed that subjects are not separable according to their gestures. This suggests that subjects had a good degree of consistency between them, and very little consistency between gestures.

Similarly, the 2 PCs are also plotted for the reduced representation, in fig. 6c. The separability between gestures is not as high, but still present. In comparison, the 2 PCs are plotted for the magnitude autocorrelation in fig. 6d, and it can be seen that some gestures are much closer together, while several strokes of the same gesture are further apart.

Since our reduced inter-axis correlation representation is 2-dimensional, i.e.

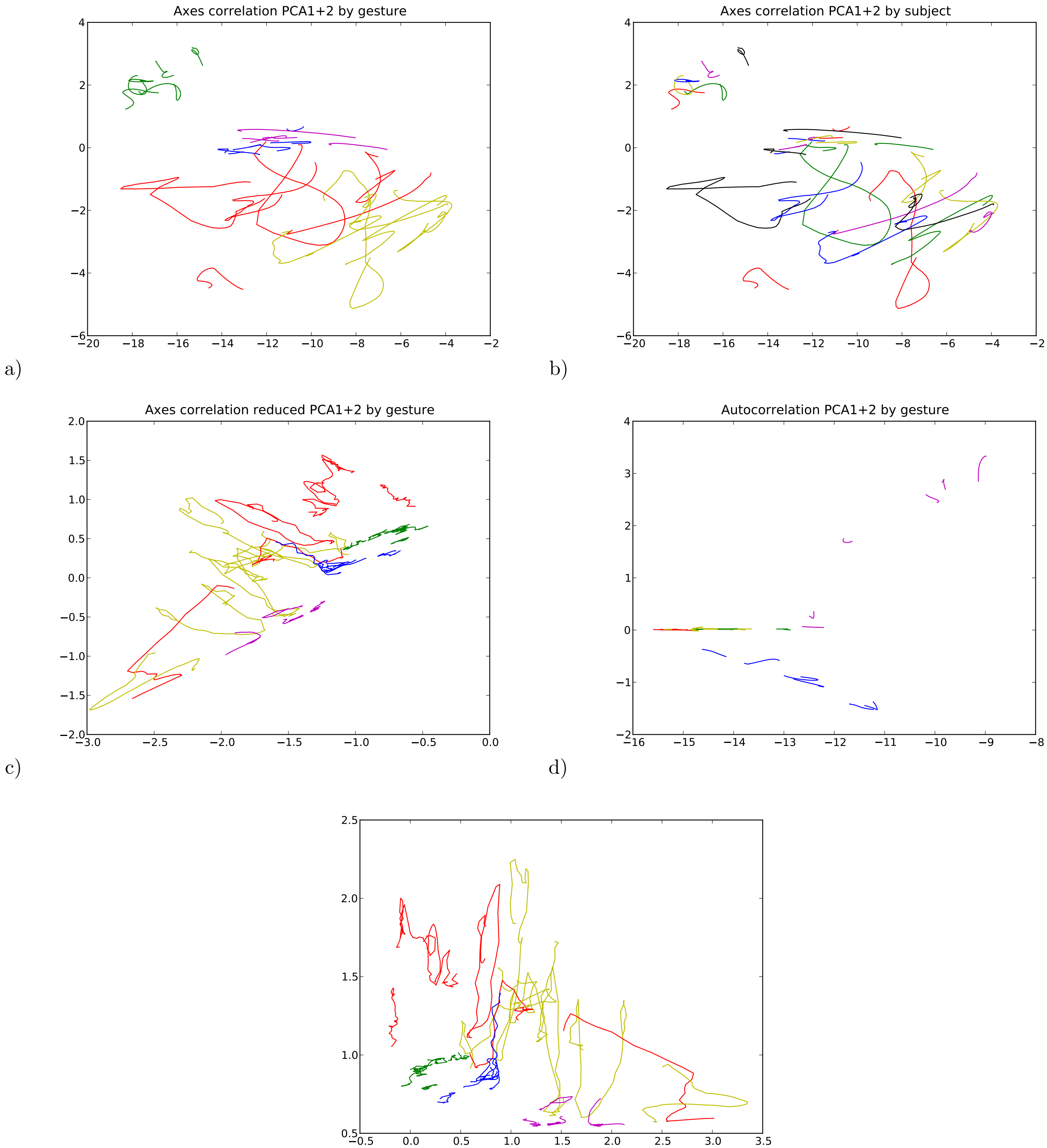


Figure 6: Two first principal components of: (a) Inter-axis correlation coloured by gesture, (b) coloured by subject, (c) Reduced representation of inter-axis correlation coloured by gesture, (d) Autocorrelation coloured by gesture. (e) Reduced inter-axis correlation measures without PCA.

the spectral centroid and slope, we can also show this plot for comparison with PCA. In fig. 6e, it is clear that PCA transformation is not needed for this representation, since it is already nicely separable by gesture. Indeed, the PCA essentially just provides a simple rotation of this space.

Overall, the results of PCA seem to indicate a good agreement with our ANN-based classification analysis presented above. However, PCA lends itself nicely to lower-dimensional representation, which will come in handy during the discussion of visualization, below.

As mentioned, however, it is still to verify that these techniques apply well to general, unstructured accelerometer data as we might receive from sensors in smartphones for example. Larger data sets may be needed, and in that case comparison with reliable tags may be impossible, therefore unsupervised methods may be preferred. Unfortunately, without tags, it will nonetheless be difficult to infer *meaning* in the results of unsupervised methods. But a large data set may help to establish points of interest and general boundaries of a PCA space that we may wish our system to react to.

3 Dynamic systems

In addition to data analysis, an important component of the *e[m]erge* project is the use of dynamic systems to react to sensor data and provide feedback by means of media control. We have developed two systems which can work together or independently to provide a dynamic response to sensor input.

The first is a library for agent-based behaviour, written by Sofian, called Qualia. The other is a shared environment called Influence, written by Joe and Steve, which uses a pixel-based, GPU-driven 2-D convolution process to iteratively transmit information between agents that inhabit the space. Using libmapper as a communication protocol, Qualia can control agents which inhabit the Influence environment, but Influence can also be inhabited by agents reacting in a purely physical manner (particles), or by agents controlled externally by human input.

3.1 Qualia

Qualia is a C++ library which provides a framework for development of agent-based logic. In particular, it implements subsystems for reinforcement learning and for state machines.

Reinforcement learning is an interesting approach because the designer need not understand the mechanics of the agent's decision making process. Rather, the designer can focus on what the intended behaviour is by creating a "reward function," which rewards the agent for good behaviour and punishes it for bad behaviour. Over time, the agent will learn to associate its own actions and its observations of its environment with good or bad behaviour, and try to perform "good" actions.

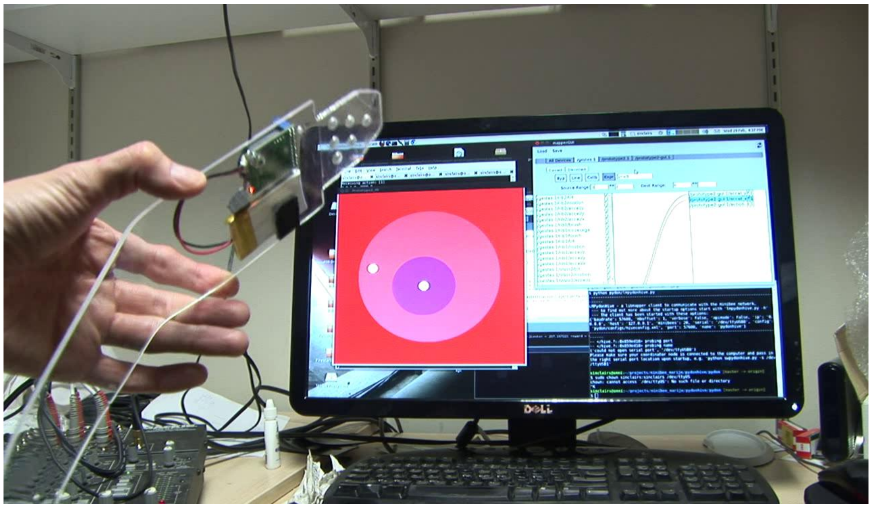


Figure 7: Qualia interacting with a human.

In order to test the idea as an interactive system, we decided to implement a simple one-on-one interaction between a Qualia agent and a human. An applet was developed in Processing which accepted human input via mouse motion and button state. A circle was made to follow the human by applying spring forces towards the mouse position, and the mouse button state controlled the polarity of a virtual magnet attached to this circle.

The agent also controlled a circle, and its action could only turn the magnet on and off. Therefore if the polarities of the human and agent were the same, the agent would be attracted towards the human, or otherwise repelled. The reward function was designed to reward the agent for getting close to the human within a certain radius, however, if this radius was surpassed and the agent got too close, it would be punished heavily. Therefore the agent tried to learn how to approach the human without getting too close. Later, we allowed the human to control the system using a Minibee, pictured in Fig. 7.

The impression was interesting. Although the agent is clearly trying to get close, it feels very tentative at first. However, this encourages the human to try to "taunt" the agent and bring it out into the center. We also found that it sometimes ended up in corners, therefore we added rules to punish it for being too close to the sides.

After some time, we found that we started to play with the agent, trying to attract it and see how close we could get. In other words, we started playing a collaborative game with the agent. The magnetic physics caused the agent to fly away quite quickly when it came too close, due to the distance-squared forces, which added to the fun.

This system also demonstrated the use of libmapper as a transport layer between an agent, an environment, and a human. Qualia, the Processing applet, and the Minibee ran in different processes, usually on different computers in the IDMIL.

Next, we planned to determine how to scale this interactive design in order to involve multiple users and multiple agents. This led to the development of the Influence environment, detailed in the next section.

3.2 The Influence environment

An immediate idea for involving multiple agents was to have them connect to the Processing environment just like the original Qualia agent, and have the Processing physics engine apply forces between them. However, with a mind towards generalization and scalability, we wanted to make such an environment where the motion of agents was determined mostly by the agents rather than the central process, so that no one process was in charge of integrating all the physics. In the setup above, the physics engine inside the Processing applet would be in charge of an N-body physical problem, which may not scale well to large numbers of agents.

Additionally, although the physical motion was an interesting interaction, we wanted an environment which could be used in a more general way, to inform agents of their surroundings and allow them to make decisions on how to act, without needing to implement globals laws such as a physical simulation. The reason is that the locations of agents in this space will not necessarily represent physical positions, but may indeed be used to represent characteristic analyses of sensor data.

Previously in the IDMIL, Joe had designed an interactive table which used a pixel-based convolution method to transmit information about what objects are on the table towards objects in a physical simulation. At each iteration, 30 frames per second, the convolution caused active pixels to spread further and further, and meanwhile a physics engine was reading the pixel data and using it to inform forces; this allowed simulated objects to be attracted or repelled by real objects seen through a camera.

We decided to use this idea to propagate information between agents. This has several advantages for our application: firstly, the N-body problem enabling all agents to "see" all other agents is spread across time, so that it becomes a linear problem in the number of pixels rather than agents. Although this could be represent considerable amount of processing, we implemented the convolution in a GPU shader, off-loading the work from the CPU. Since it does not increase with the number of agents, as long as the GPU can handle the workload, computational requirements are constant. Secondly, since interaction takes place in a 2-D bitmap, it lends itself to other methods of interaction, such as drawing directly on the surface, placing virtual walls or objects in the space, or taking input from a video or depth camera such as the Microsoft Kinect.

The current implementation features 2-D vector fields that support directionality, enabling effects such as spin and flow. The user can draw flows with the mouse that pull agents along a path. Currently we have connected physical agents that simply react to observations, the values in surrounding pixels, with

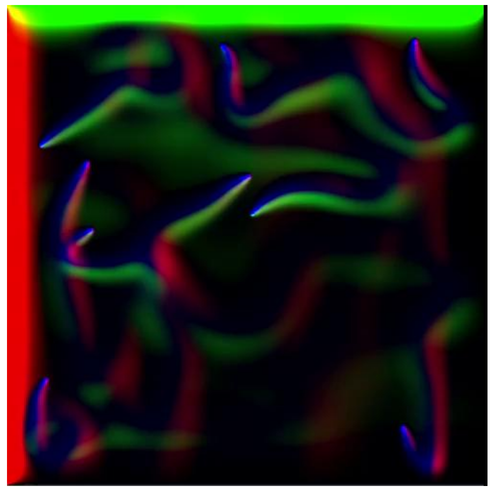


Figure 8: The Influence environment with several physical agents connected.

force in some direction. It can be seen in Fig. 8 that the agents leave trails. This is because as they move, they write values to the vector field which decay over time.

At the Moment Factory work session in May, we have also connected a Qualia agent and used MF's X-Agora software to display agent positions by mapping to it using the libmapper GUI. The Qualia agent did not behave in an interesting way, so the reward function needs work, however as a proof of concept the trial was successful.

There are some limitations. Since they also write in front of themselves, they tend to see their own influence, which limits the speed at which they can move. Additionally, an agent in motion can only affect agents that happen to move behind it. It is possible to use additional passes or larger convolution kernels to increase the speed of influence propagation, however this has strange effects on their motion, again due to them seeing their own influence.

Nonetheless, Joe has implemented some test environments with large numbers of local agents, which can be seen in Fig. 9. These show that interesting emergent behaviour can arise by having one or two types of agents with simple sets of rules.

Even if the cited limitations pose a problem, Influence presents a proof of concept dynamic environment where agents of different types can inhabit and observe each other. A physical environment such as a gravity simulation could provide similar communication. Either way agents will need a way to summarize information about surrounding agents such that their information can be reduced to a constant-sized vector which can be processed by some decision engine such as Qualia's reinforcement learning.

We have shown that a dynamic system can be fed information from sensors, simulations, and intelligent agents, such that they observe each others behaviour

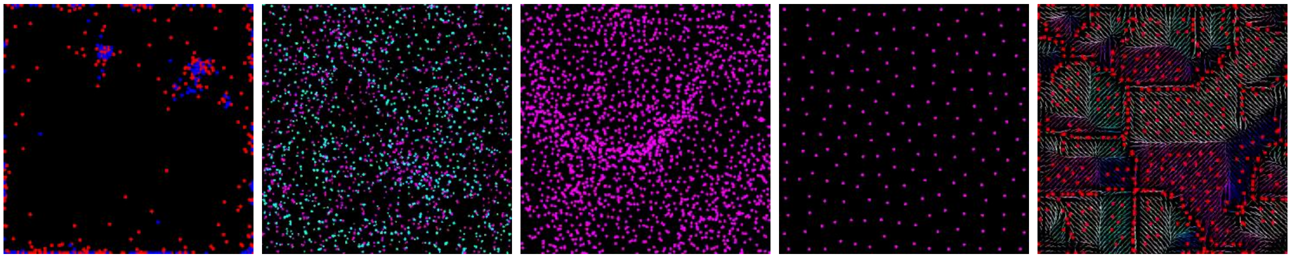


Figure 9: Large numbers of physical agents in the Influence environment creating various emergent effects. Left to right: quasi-stable molecules form; opposing flows; flows give rise to waves; stable repulsion; spacial division into membranes filled with repulsive particles.

and react.

A possible use case for this software will be to use agent positions to represent data other than physical position. For example, the PCA transform used to analyse the gesture data in section 2.2.4 may be applied to incoming sensor data and used to position agents within the Influence environment. Since their position now represents the gestural activity, after a short moment agents will be able to tell that there are other agents behaving in a similar manner.

A reinforcement agent could notice that its actions cause activity in a certain region, and respond with some media to encourage more human agents towards a given location, or attempt to disperse them from some activity that is getting boring.

3.2.1 Scalability

Currently Influence can be connected with tens of agents, it has been run with about 100 agents connected at once. In the future we would like to connect many more agents. This is mostly a communication bottleneck; if some agents such as physical agents or Qualia agents are run locally to the process, many more can be supported, as Joe has shown by running thousands of physical agents in real time.

Therefore if network communication is reserved for sensor-based agents and off-loaded computation only if necessary, we estimate being able to increase the total number of agents in the system. Eventually we expect that the number of sensors connected to a single computer will be the main restriction. At that point, ideas for expanding the environment idea to a decentralized approach will be necessary; these include stitching together several Influence environments running on separate computers by transmitting border pixels, or having other methods of multiple Influence environments to perturb each other. (E.g. agents which jump from one environment to another depending on some state.)

In any case, if this kind of interactivity is to scale to thousands or tens of thousands of cell phones for example, more serious consideration to hardware

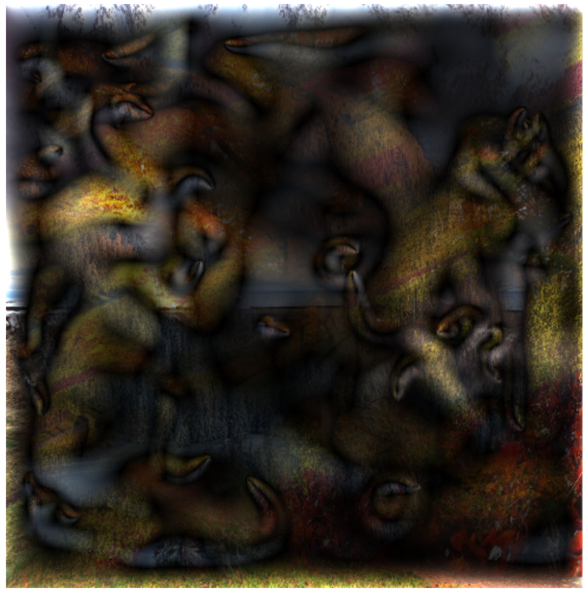


Figure 10: The Influence environment with images of 4 seasons mapped to the colour space used to maintain the vector fields.

and software designed for this purpose will be required.

4 Visualization and media

Thus far not much thought has gone towards visualization and media throughout the *e[m]erge* project, however consideration of interacting with content is a necessary project goal.

One very simple idea has been to take the natural colour mapping used in Influence and use this to map images to a video feed. An example is given in Fig. 10, where images of the four seasons were downloaded from Flickr and blended according to rules governed by the pixel colours.

Another idea has been to project the agents on the floor, and use a Kinect feed to have physical or intelligent agents swarm around detected humans and objects.

However, more seriously we presume that the positions of agents and their influence will not be directly mapped to media, but will be used to observe activity in certain regions of the gesture space. This will indirectly control some media through decision logic, either intelligent or explicitly designed, to encourage or discourage such activiy, as suggested above. They may consist of dimming or brightening lights, controlling video projections, or anything else. This part of the project is still under discussion, however progress has been made in connect other *e[m]erge* projects to X-Agora via libmapper.

5 Libmapper progress

Throughout the work described in previous sections, libmapper, liblo, and surrounding software have seen a great amount of attention toward supporting current and future *e[m]erge* development.

Libmapper has been completely ported to Windows, currently compiling using the MingW/MSYS Unix-like environment for Windows. Visual Studio support for libmapper is in the works, since it has been requested by Moment Factory. It has not been immediate since it means removing some C99'isms in the code base which are not supported by the Microsoft C compiler.

Tentatively, Android support has also been in the works. Mostly liblo has been made to compile in the Android NDK, however testing of libmapper is still down the line. Moment Factory's current interest in cell phones is over the HTML5 mobile API, therefore getting native support into Android and iOS has not been a major priority.

Additionally, as mentioned above, Moment Factory's contribution has been to incorporate libmapper into their X-Agora software via the built-in Lua interpreter, work done by Bruno Angeles, which allows remote programs such as Influence to control elements in its scenegraph for visualization purposes. In the MF work session in May, we also used their HTML5 back-end with libmapper through the Max/MSP object, which has been ported to Windows for this purpose.

The major undertaking for libmapper itself in the last few months has been Joe's work on the "instances" feature, which will lend itself well to the Influence environment in order to support an arbitrary number of agents. This feature is also necessary for other libmapper purposes, such as to support multitouch mapping and polyphony in musical contexts.

Instances have been working for some time, but not yet integrated into the main development branch due to continuing thought toward design decisions, as well as difficulty finding time for the team to fully review code changes, which are non-trivial. Recently, experience with bidirectional communication between agents and Influence have also led to some surprisingly tricky issues in the connection logic which are currently being ironed out. For details we refer the reader to the libmapper mailing list where discussion is on-going.

Currently we are successfully testing ideas in Influence without instances, but when instances are made available in the main code branch it will ease testing, experimental mapping, and scalability when dealing with large numbers of remote agents.

6 Vibrotactile feedback

As a somewhat peripheral project, Marcello Giordano (IDMIL) has investigated control of the Android vibration API. He has designed an application which can respond to user interaction or incoming OSC messages to stimulate vibration signals to the user.

This could be used in the future as a response mechanism in synchrony with media, or could be used directly for cell phone interaction to encourage usage of gaming interfaces for interactive control of an agent.

7 Conclusion

To date we have managed to find methods for reducing dimensionality of correlations based on accelerometer data, and incorporated these results into real-time controls for agents in a dynamic system. Examining the working *e[m]erge* system diagram, Fig. 11, we can see that most of the boxes have been covered thus far.

Data Collection has been addressed by the Minibees and continued work on cell phone integration at MF. Feature extraction has been examined in a lab context and successfully used to determine salient features, though it continues to be a point of research in regards to more natural data.

Off-line visualization and classification have been used to examine salience of data analysis methods. In the "field," it may be interesting to develop real-time PCA tools or other unsupervised methods for active visualization of crowd behaviour.

We have developed dynamic systems and intelligent agents able to react and interact with sensor data. Although all these directions will continue to require research and development, it is clear that the main focus left for this project is to integrate the above systems into active media control.

This is planned as a major upcoming subject for the next *e[m]erge* meeting and an active topic through the summer to wrap up the project.

References

[1] A. V. Barbosa, R.-M. Dchaine, E. Vatikiotis-Bateson, and H. C. Yehia. Quantifying time-varying coordination of multimodal speech signals using correlation map analysis. *JASA*, 131(3), 2012.

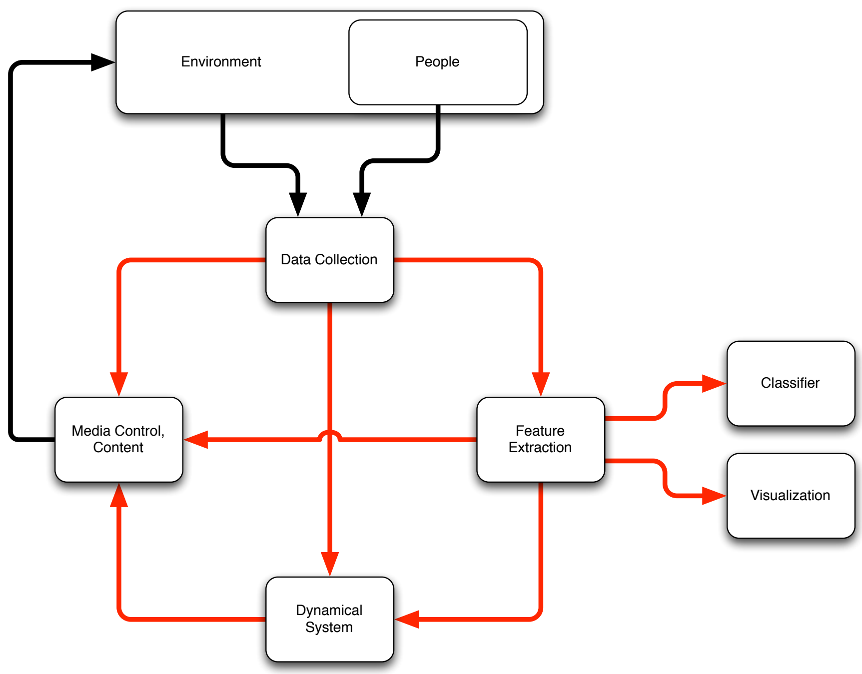


Figure 11: System diagram for *e[m]erge*.